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STRUCTURE, COSTS AND PERFORMANCE IN CANADIAN FOOD AND BEVERAGE INDUSTRIES: INTRA-INDUSTRY AND INTER-INDUSTRY STUDIES[1]

(Working Paper 3/89)

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January 1989

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ABSTRACT

In this paper we use three quite different methods to look at the effects of structure - mainly industrial concentration, or firm output share distributions - on output prices and costs of production in 17 Canadian food and beverage industries. Our results indicate that quite a number of industries have displayed non-competitive behaviour over the past two decades or so. We are able to show that in the high-concentration industries (those with Herfindahl indices greater than 10 on average, or about half the industries studied), costs of production tended to rise when concentration increased; likewise costs tended to fall when concentration decreased. The opposite was generally true in low-concentration industries (those with Herfindahl indices less than 10 on average). The strong link observed between concentration and costs implies that mergers in high-concentration industries which would tend to increase concentration are likely to increase costs, suggesting that the efficiency defence of the Canadian Competition Act may not be warranted in such cases. We also conclude that mergers of the sort which increase concentration are likely to raise both product prices and costs of production in five industries: flour and breakfast cereals, biscuits manufacturers, confectionery manufacturers, distilleries and breweries. From an economic standpoint, mergers which increase concentration in these industries would almost certainly be detrimental to society.

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ACKNOWLEDGEMENTS

Over the course of this research, we have received assistance and helpful suggestions from a number of people. We would particularly like to thank John Baldwin and Paul Gorecki for the use of part of their database and John Heath and John McVey for estimation that they did for us with the microdata we used. Brad Gilmour, Louise Hunt and Yves Surry provided very useful observations and stimulating discussions regarding both content and style of an initial draft of this paper. M. Salem and Don West are thanked for their comments and encouragement during the original project. And Micheline Doth typed most of the text with great accuracy and efficiency. Needless to say, all remaining errors and omissions are ours alone.

1. INTRODUCTION

In the formulation and application of industrial policy, it is important that policy-makers be provided with information which will help them in directing their programs where assistance or regulation is needed most. The purpose of the three studies which comprise this paper is to contribute to the policy-making process by identifying possible sources of concern in the Canadian food and beverage sector with respect to structure, productivity and profitability performance. We adopt a selection of methods in an attempt to fill a number of significant gaps in knowledge regarding costs of production and product pricing in the 17 or so industries which make up this sector. Most particularly, we focus on the extent to which changes in structure within the sector (i.e., changes in the way that firms share industry output) have been connected with efficiency and market power (the degree to which firms have been able to raise prices above costs in a significant way).

Both efficiency and market power effects have reference to monopoly, or the tendency towards it, since as firms become more able to set the price at which they produce, they may also be less likely to choose cost-efficient levels of output (i.e. the output level suggested by perfect competition). Divergences in behaviour from price-taking and cost minimization imply waste, overall welfare losses and transfers of wealth from consumers to producers. If such divergences can be identified and if they are considered to be important, policies which can reduce or eliminate these types of behaviour ought to be formulated. In using this approach to identify 'problem' industries, we provide the basis for policy action. And, by defining the sources of these problems, we are able to narrow the necessary scope of such policies so that formulation can be made more problem-specific and so that possible trade-offs are better known.

Three distinct approaches are taken in fulfilling the above-mentioned objectives. The first study (Chapter 2) examines differences in profitability from an 'industrial organization' (IO) perspective. The IO approach is used to yield insights regarding the possible causes of differential levels of market performance (profitability) between food processing industries. The analytical framework we employ here is fairly standard, in the sense that 'structural' factors such as concentration, protection from import competition, and barriers to entry of new firms are linked to profitability, with implications drawn out for the important issue of whether differences in profitability across industries are due to differences in prices (market power) or in costs (efficiency). We depart, however, from traditional cross-sectional empirical approaches that draw inferences from estimated parameters (obtained by fitting equations to data for all or some groups of industries being studied). Instead, we construct brief case studies for each industry using a variety of information without employing estimation techniques. We then classify the industries into various categories, ranging from 'workably competitive' to 'market power'. Although this 'morphological' approach lacks the rigour of a formal model, it does help in establishing which industries are profitable mainly due to efficiency and those profitable mainly due to the exercising of market power. By using firm-level rather than industry-level data we are also able to exploit information about differences between firms, and can show how these firm-level differences can imply significant dissimilarities between the way in which we view industries.

In Chapter 3, productivity (or efficiency) issues are examined with firm-level data. Here, instead of examining a 'snapshot' of industrial performance at a point in time (actually averaged over the three years 1977, 1978 and 1979, in Chapter 2), we focus on **changes** in productivity, over the 1970-79 decade (the longest period for which microdata are currently available). Whereas the neoclassical theory of productivity and economic growth assumes that aggregate, or industry-level productivity changes are driven by within-firm events (such as technical change), we also consider other effects. Again, we follow the industrial organization approach in explaining the behaviour of firms, which, although less familiar than the neoclassical approach, does suggest that other factors could be at work. In particular, an industry's productivity growth performance may be affected by structural changes, such as the entry of new (and presumably more productive) firms, exit of high-cost firms, and shifts of output shares between relatively high-and low-cost firms within the industry. In order to measure the relative contributions of within-firm versus across-firm effects, we use an 'accounting' framework to keep the two components separate and compare these to see which has been most influential in changing productivity in each industry.

In Chapter 5, the final study adopts a quite different approach from the first two, although we extend both analyses in different respects. Here, we use industry-level data to measure the effects of concentration changes (approximately the inter-firm share effects of Chapter 3) on costs, using a translog cost function adapted for these purposes. The more formal model used here helps us examine the different possible ways that concentration changes (i.e. changes in the way that firms in an industry share output) are linked to costs. It also provides useful information for purposes other than structural policy, such as elasticities of factor demands and estimated returns to scale, thereby contributing to a more complete understanding of how these industries work.

In the final chapter of this paper, we summarize the results of all three studies, and identify those industries which ought to be of most concern to policy-makers and where additional attention is deserved. We also attempt to resolve some inconsistent results between the three approaches, so that an overall consensus can be reached for as many industries as possible.

2. COMPARING STRUCTURE IN FOOD AND BEVERAGE INDUSTRIES: INDUSTRY CLASSIFICATIONS USING FIRM-LEVEL DATA

2.1 Introduction

In this chapter we employ information drawn from firm-level data to show how sixteen 4-digit food and beverage industries can be classified in terms of the structure-conduct-performance paradigm. Using a number of indices for each industry, we combine these to define a number of general classifications ranging from 'workably competitive' to 'market power'. These classifications help in identifying which food and beverage industries are closest to displaying 'competitive' behaviour and therefore are most desirable from an economic standpoint, and which do not (and may be more adequately described as oligopolies or 'non-competitive' industries). It is the non-competitive group of industries which is of most interest to policy-makers, since it is here where the greatest resource use distortions and price distortions occur, relative to the perfectly competitive 'ideal'. What we shall focus on here is the extent to which differences in profitability between food and beverage industries can be explained by certain facts about each industry.

Traditionally, within the industrial organization (IO) paradigm, profitability differences have been associated with differences in profit markups rather than differences in costs. In particular, it was believed that market structure - especially seller concentration - determined the success of firms in an industry in raising prices above costs (oligopolistic conduct), with correspondingly unfavourable implications for market performance (income distribution and overall efficiency).

The oligopoly-pricing model has been challenged, especially by Demsetz (1973), who posited that higher profits often observed in concentrated industries and often attributed to market power, in fact reflected differences in cost efficiencies between leading firms with large shares of industry output and remaining firms in the industry. Demsetz asserted that any association between concentration and profitability is actually more likely to be due to the natural propensity of more efficient, lower-cost firms to grow relatively large - thereby increasing concentration - and earn higher profits through their relative efficiency alone.

In the oligopoly model, on the other hand, bigger firms are not necessarily more efficient than other firms, and may even have higher-than-average costs, due to 'monopoly slack'. However, their size gives them power, which they use to increase prices and thus profits. Depending on how differentiated are the products sold by different firms in an industry, the oligopolists may just raise their own prices or they may pull up the price structure of the entire industry, benefitting smaller firms as well. In any case, the result will be that industry-level data show a correlation between concentration (proxying the presence of firms with big enough market shares to act successfully as price-raising oligopolists) and profitability.

Up until recently, it has been difficult to decide empirically between the validity of the oligopoly pricing and the cost-difference explanations of profitability differences, because only industry-level data have been available. With the firm-level data that we use in this study, we are better able to sort out these effects and establish which are dominant.

2.2 Data Description and Summary Indices

The main source for the data used here is the annual Census of Manufactures carried out by Statistics Canada. Each firm in each industry is asked for details on its sales revenues, materials and fuels costs, wages and salaries and levels of employment. Additional data on capital intensity, tariffs and foreign trade, and advertising expenditures, were collected from other Statistics Canada sources by John Baldwin and Paul Gorecki, and made available to us by them. Data for firms within each of all of the 18 4-digit food and beverage industries were available but we excluded the miscellaneous food processors industry given that data for it are likely to be too heterogeneous to make useful inferences from. The wineries industry was also excluded due to its small size (fewer than one thousand employees).

We use the everyday word 'firm' to correspond to what Statistics Canada calls an 'enterprise', defined by them as a "company or family of companies which, as a result of common ownership, are controlled or managed by the same interests" (Statistics Canada, cat. # 31-528, June 1979, p. 17). The Census does not attempt the very difficult job of extracting direct information on unit prices and costs from the respondents[1], so this information is inferred from the profit margin data which we compute from the total revenue and cost information collected in the Census.

Unless specified otherwise in the definitions, our representative data are averaged over the three years 1977, 1978 and 1979. This was done to reduce the amount of 'noisiness' due to cyclical or random fluctuations in each year's data. 1979 is the most recent year for which John McVey's Microdata section has constructed the firm-level database. We used these data to construct a number of summary statistics for each of the 16 industries studied. Results of these calculations are given in Table 1; a brief definition of each entry is given below.

Average Profit Margin: This is the percentage ratio of profits to value of production (the profits/sales ratio) where profits are the difference between value of production and the sum of materials, fuels, wages and salaries, and capital costs. All data are from the Census of Manufactures except capital costs, which are imputed as 0.04xindustry capital stock (0.04 is an estimate of the 'normal' or competitive real rate of return in Canadian food and beverage industries). The figure in brackets is the ratio of profits to value added (value of production minus materials and fuels expenses).

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[1] Although they do collect 'unit value' data for specified classes of products within each industry. At some effort and expense (because the classifications are, of course, different for each industry), these unit value data could yield information on intra-industry differences in non-quality adjusted prices.

Table 1: Performance and Structure of Canadian Food and Beverage Industries, 1977-1979

(SIC)	1 Average Profit Margin	2 Profit Hetero-geneity	3 Fringe Profit-ability	4 Index of Natural Entry Barriers	5 4-firm Seller Concentration ratio, 1979	6 Relative Size of low-profit-ability firms	7 Average Firm Size $Millions 1979	8 Number of firms, 1979	9 Capital/ Output Ratio	10 % Tariff Rate 1978	11 % Advertising Sales Ratio 1977	12 Share of Market 1979 Imported	13 Share of Output Exported	14 Value Added Shipments Ratio
1011 Slaughtering and Meat Processors	6.9 (40)	0.23	L	0.58	44	0.61	15.2	469	0.29	2.0	0.0	0.06 (75)	0.10	0.173
1012 Poultry Processors	8.1 (32)	0.25	L	0.60	38	2.03	14.7	71	0.40	10.0	0.0	0.03 (85)	0.00	0.256
1020 Fish Prod. Ind.	12.6 (33)	0.32	L	0.93	45	0.39	7.3	277	0.54	4.0	0.0	0.22 (46)	0.53	0.377
1031 Fruit & Veg. Canners & Pres.	16.9 (45)	0.35	L	0.95	41	0.18	8.6	154	0.93	5.0	3.0	0.24 (66)	0.04	0.379
1032 Frozen Fruit & Veg. Proc.	17.8 (49)	0.37	M	0.09	61	0.23	11.1	30	1.19	5.0	3.0	0.34 (61)	0.13	0.365
1040 Dairy Prod. Ind.	11.1 (46)	0.18	L	0.28	36	0.49	14.6	303	0.49	4.0	1.0	0.02(100)	0.03	0.242
1050 Flour & Breakfast Cereal Prod. Ind.	15.5 (51)	0.33	L	0.36	66	2.33	33.5	31	1.46	7.0	4.0	0.05 (94)	0.29	0.303
1060 Feed Industry	9.7 (49)	0.26	L	0.33	26	0.41	4.4	485	0.56	3.0	1.0	0.02 (71)	0.04	0.198
1071 Biscuits Mfrs.	16.8 (34)	0.18	M	0.30	74	1.27	19.8	23	0.73	5.0	2.0	0.06 (54)	0.05	0.492
1072 Bakeries	15.5 (29)	0.34	L	1.06	33	0.61	0.8	1551	1.17	8.0	1.0	0.02 (57)	0.02	0.543
1081 Confectionery Mfrs.	27.8 (57)	0.55	M	0.99	50	0.32	7.0	104	0.77	7.0	4.0	0.19 (62)	0.05	0.486
1082 Cane and Beet Sugar Processors	12.6 (51)	0.22	L	0.19	85	-	65.2	8	0.30	1.0	0.0	0.38 (13)	0.11	0.245
1083 Veg. Oil Mills	5.1 (46)	0.06	L	0.10	78	3.00	90.9	9	0.69	2.0	0.0	0.32 (15)	0.17	0.172
1091 Soft Drink Mfrs.	17.6 (36)	0.35	L	0.95	48	1.22	6.2	200	1.16	6.0	5.0	0.01 (50)	0.00	0.488
1092 Distilleries	39.1 (62)	0.25	M	0.86	77	0.49	4.4	16	1.64	50.0	4.0	0.25 (9)	0.24	0.632
1093 Breweries	34.3 (49)	0.20	M	0.10	99	2.03	138.7	8	2.48	16.0	6.0	0.01 (9)	0.06	0.701
All Food and Beverage, Average	16.7 (53)	0.27		0.54	56	0.61	30.0	234	0.93	5.3*	2.1	0.14	0.13	0.315
All Manufacturing Average	16.5 (41)	0.50	0.7	0.80	53	0.82	31.5	174	1.17	9.6	1.2	0.23	0.18	0.401

Source: Special Statistics Canada tabulations and database of John Baldwin and Paul Gorecki.

* Column 10 average for all food and beverage excludes SIC 1092.
'All food and beverage' and 'All manufacturing' are unweighted averages (except column 14).

The number in beckets beside column 1 are profit margins on value added. The numbers in brackets beside column 12 are the percentage of imports subject to tariff duties at the average rate shown in column 10.

Profit Heterogeneity: The difference between the profit margin of the highest-profit and the lowest-profit firm in each industry, divided by 100. Thus, if the most profitable firm had a profit margin of 50% (averaged over 1977-79) and the least profitable 10%, 'profit heterogeneity' would be 0.4.

Fringe Profitability: This is the profitability of the firm with the lowest profit margin, on average, over 1977-79, in its industry. To preserve confidentiality, actual values are not shown, and the sample is divided into three categories. Industries with 'low' (L) fringe profitability are those in which the least profitable firm had a margin less than 5 percent. 'Medium' (M) fringe profitability is set between 5 and 10 percent, and 'high' (H) fringe profitability exceeds 10 percent.

Index of Natural Entry Barriers: When the firms within an industry are ranked from highest- to lowest-profit margin, a histogram can be drawn, with the width of each firm's segment equal to the proportion it takes of total industry output. This is illustrated on Figure 1 on which we put 'unit costs' (= 1 - profit margin) on the vertical axis. That is, we have a ranking of the firms from lowestto highest-unit costs.

This histogram gives us a picture of the industry's internal cost structure. Unfortunately, for reasons of confidentiality, we are not permitted to show these histograms, since they might allow identification of individual firms. but we can summarize the information they contain by approximating them with a smooth line, fitted by least squares to the actual unit cost-output shares data (see Figure 2). It was found that a cubic function of output shares gave a good fit to the histograms

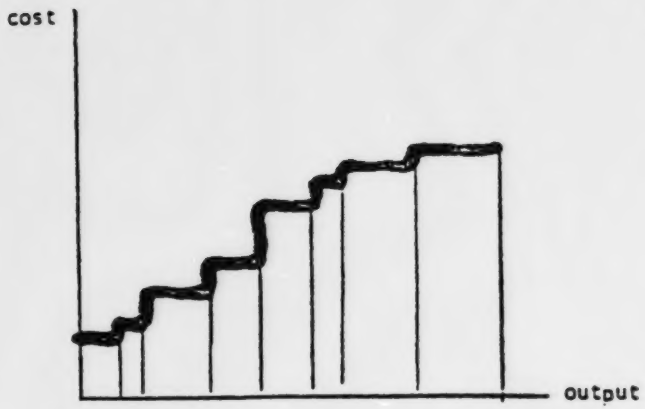

fig. 1: unit cost distribution histogram

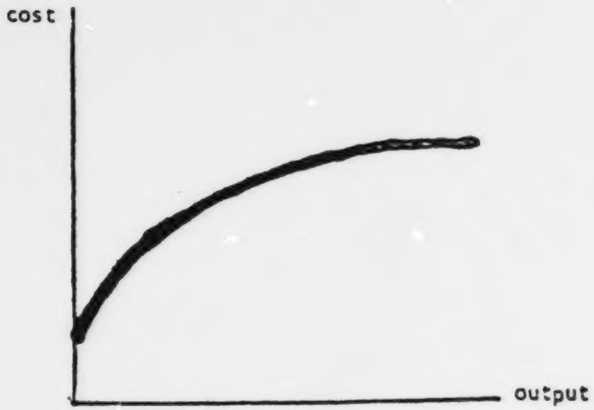

fig. 2: smooth approximation to cost distribution

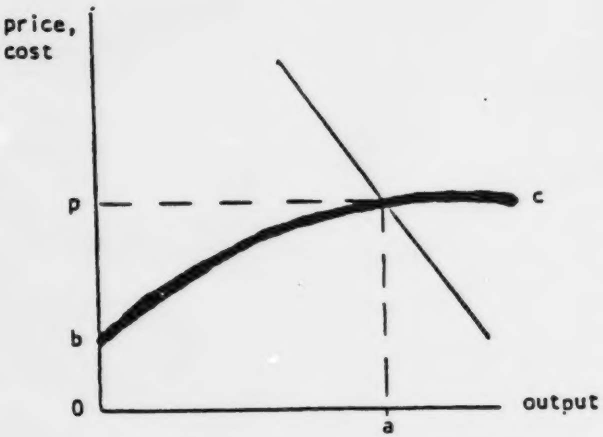
price, cost
p
b
0
c
a
output

fig. 3: heterogeneous-cost contestability

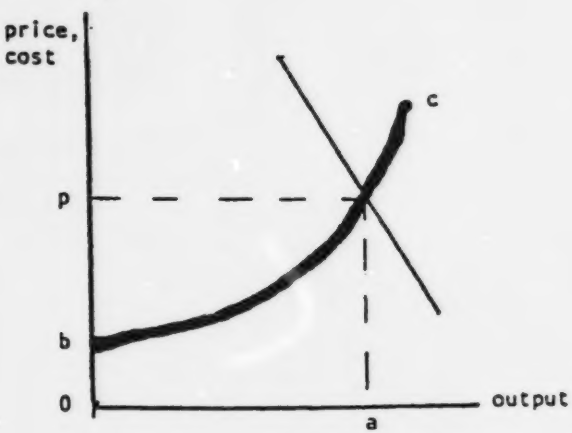
price, cost
p
b
0
c
a
output

fig. 4: naturally barred industry

for the majority of industries.

A particular interesting characteristic of these 'cost distribution functions' is their slope at the high-cost (low profit or 'fringe') margin. Although we cannot observe the implicit costs facing potential entrants, it is reasonable to assume that the supply curve for new firms is not 'discontinuous' with the shape of the cost distribution just within the high-cost margin.

If so, then an industry with a cost distribution that is relatively flat at the high-cost margin (as in Figures 2 and 3) may be expected to have an elastic supply of potential entrants who could operate in the industry with costs not much greater than the costs of those high-cost firms already in the industry (and surviving through the 1977-79 period).

Alternatively, if the cost distribution is steep at the margin, we could infer that the supply of potential entrants - of firms that could profitably operate in the industry at a slightly higher price - is relatively inelastic, as in Figure 4. We call industries with steep cost distributions at the margin 'naturally barred', meaning that entry to them is restricted or barred not by anti-competitive conduct on the part of incumbent firms, but by a shortage of new firms able to match the cost performance of tre present operators. We will have more to say on this in Section 2.2.

The 'index of natural entry barriers', then, is measured as the elasticity of the fitted cubic cost distribution evaluated at the high-cost end of the distribution. A value larger than one implies that a one percent increase in industry capacity would require admitting into the industry a firm or firms with unit costs more than one percent higher than those of the current highest-cost firm.

4-Firm Seller Concentration Ratio: This is the familiar measure of the extent to which an industry's output is dominated by its largest firms, being the percentage of sales accounted for by the largest sellers.

Relative Size of Low-Profitability Firms: We split the industry's cost histogram into two halves (as on Figure 1), then calculate the average firm size (output per firm) in each half. The ratio of low-profit to high-profit average firm sizes is the relative size of low-profitability firms, which may proxy the extent to which scale economies are important in the industry.

Average Firm Size: Industry value of production (value of 'gross' output) divided by the number of firms, 1979, millions. Note that value of production is not identical to value of shipments - the two measures differ by the amount of any net change in inventories that occurs during the year.

Capital/Output Ratio: Gross end-year capital stock (value of structures, machinery and equipment) divided by industry gross output.

% Tariff Rate: Calculated as the percentage ratio of the value of duties collected to the value of dutiable imports (including duties collected) of products classified to the industry's SIC, 1978.

% Advertising/Sales Ratio: Estimate of the industry's expenditure on advertising services as a percentage of total sales revenue, 1977.

Share of Market Imported: Ratio of imports to total Canadian sales, 1979. The number in brackets is the percentage of imports that were subject to tariff duties.

Share of Output Exported: The ratio of exports to the domestic (Canadian) industry's output, 1979.

Using these results we shall try to classify industries using the following general categories:

(a) pure oligopolistic market power, such that incumbent firms are able to raise price above marginal cost, despite the presence of potential entrants with costs no higher than incumbents' (Figure 5);

(b) pure cost-heterogeneity, with entrants 'naturally barred' because they can't produce at low enough cost (Figure 4);

(c) a mixture of market power and cost heterogeneity (see figure 6); and

(d) those 'workably competitive' industries which do not earn a significant margin of profits over normal profit rates (and therefore have little room for any cost heterogeneity), as depicted in extreme form on Figure 7.

First, however, it is useful to compare results for the whole of food and beverage industries against those for all-of-manufacturing.

Using information in the first four columns of Table 1, we see that, overall, food and beverage profitability (adjusted for capital intensity as described in the definition of profit margins, above) is just about the same as the all-manufacturing

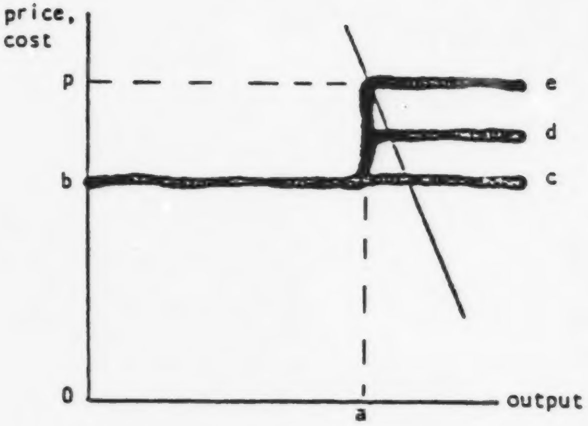

fig. 5: equal-cost with market power

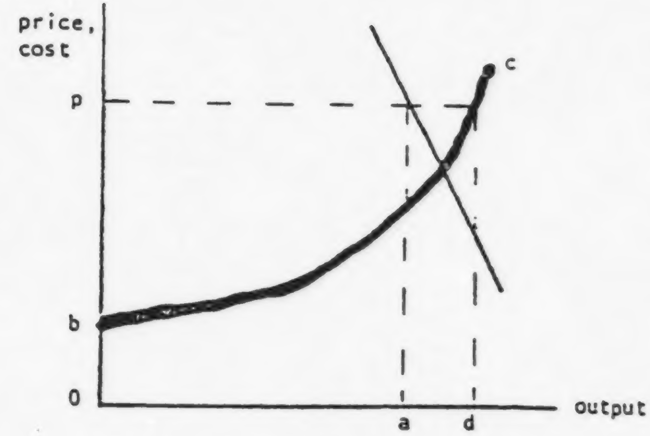

fig. 6: naturally barred with deterred entry

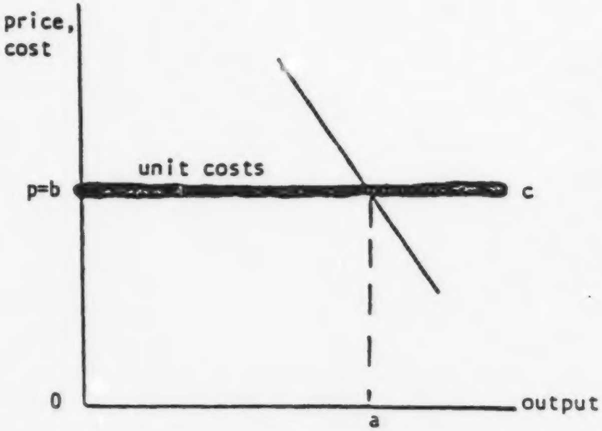

fig. 7: constant-cost contestability

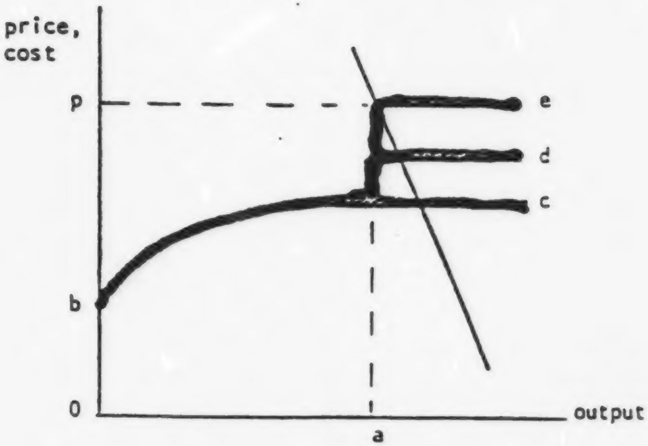

fig. 8: heterogeneous-cost deterred entry

mean, at 16.7%. However, the internal cost distributions are markedly less heterogeneous in food and beverages - the average difference in profit margins of highest- and lowest-profit firms is only a little more than half the average for all manufacturing. Along with the lower 'index of natural entry barriers' (the elasticity of the cost distribution at the low-profit fringe) in food and beverages, this suggests that technologies are relatively well-known and evenly diffused within the food and beverage sector, which is consistent with the fact that these are relatively 'mature' industries, producing products which donot change much over time.

Finding that natural entry barriers are lower in this sector than across manufacturing as a whole might imply that market power is a relatively more important source of above-competitive profit margins in the food sector (given that, overall, average profit margins are almost the same). But note that the food and beverage profitability average is pulled up by the very high margins of the two alcoholic beverage industries.

2.3 Classification Results

The results from the previous section, along with the general classification criteria (a)-(d) can now be used to characterize each industry. The outcomes are summarized below.

Slaughtering and Meat Processors: Workably Competitive

This industry has low overall profitability and a relatively homogenous internal cost structure, suggesting that its technology is relatively well-known and easily accessible to all firms. It is relatively unconcentrated (Column 5), although large firms do tend to be more profitable on average (Column 6).

Firm size and capital requirements are quite small (Columns 7 and 9), the number of firms large (Column 8), and tariffs low (Column 10). On balance, this adds up to a reasonable approximation of a perfectly competitive market structure.

One qualification to this conclusion is that meat processing is a relatively 'high turnover' industry - it adds relatively little value to its material inputs before selling them. This is shown on Column 14 of Table 1, which gives the ratio of value added to the value of shipments. If we calculate the profit margin as a ratio of value added rather than total value of output (see the numbers in brackets beside Column 1), meat processing moves from second lowest to seventh lowest in the sample.

A theoretically appropriate measure of profitability would relate a firm's profits (net of all current expenses such as consultancy payments, which are not in fact excluded from the Statistics Canada data) to the value of all the inputs tied up in the firm - including physical capital (plant, machinery), 'working' capital (to finance inventories) and possibly the 'human' capital embodied in the firm's managers. To construct such a measure has unfortunately been beyond the scope of the present study.

Poultry Processors: Workably Competitive

Most of the indicators for this industry are quite similar to those for meat processing. More profitable firms actually tend to be smaller than average (Column 6), but the cost differentials are not substantial (Column 2). One disturbing characteristic is the relatively high degree of tariff protection. But this probably just compensates for the higher input costs faced by the industry, compared with the U.S. industry, due to Canada's supply control schemes in the broiler and egg markets.

Fish Products: Heterogeneous Costs

The fish products industry earns a higher profit margin than either meat or poultry processors, but this is accounted for not by higher profits across-the-board, but by a more heterogeneous internal profit structure. That is, the difference in profitability, and hence cost performance, of the most and least successful plants is larger in this industry than in meat or poultry processing.

The better firms' cost superiority is associated with relatively larger scale (Column 6), in line with the Demsetz view of good firms doing well on both profits and market share. The large number of firms, their relatively small size, and low tariffs and tariff protection are all indicators that profitability in fish processing is not protected by barriers to new entrants.

The industry is by far the biggest exporter in food processing, in terms of destination of shipments (Column 13), but much of this success may be due to Canada's comparative advantage in catching the raw material input at relatively low cost.

Fruit and Vegetable Canners: Market Power with Heterogeneity

This is a fairly profitable industry overall, with most of the profits going to the largest firms (Column 6). The industry's low fringe profitability and heterogeneous cost structure are consistent with a fairly inelastic supply of entrants and a Demsetz-type rationale for profitability in terms of superior cost performance of larger firms. But the relatively high advertising/sales ratio, along with the size disparity between more and less profitable firms does suggest that a 'strategic groups'[2] model could also fit the data. Specifically, some of profitability of large high-profitability firms may be due to their ability to charge higher prices for nationally advertised 'name' brands, while smaller fringe plants are forced to operate on low profit margins as contract suppliers for private-label and generic brands.

Frozen Fruit and Vegetable processors: Market Power with Heterogeneity

This small industry is quite profitable. Like fruit and vegetable canners, it has a relatively heterogeneous intra-industry distribution of profitability, and its largest firms are high-profit. It also has fairly profitable fringe plants (Column 3), despite a very flat marginal cost distribution

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[2] See Caves and Porter (1977) for more on the subject of strategic groups.

(Column 4), implying that the industry does enjoy some price-raising market power. But the relatively low tariff, and high import share, (Column 12) should provide some competitive discipline to the exercise of market power.

Dairy Products: Workably Competitive

This is an industry with many firms, low concentration, fairly low profitability both on average and across the cost distribution, low natural entry barriers, and no tendency for larger firms to be relatively profitable. Thus it appears to be highly competitive. We know, however, that many dairy factories are cooperatives owned by milk suppliers, and that the low share of imports could be attributed to non-tariff trade barriers. Therefore, the industry may not be as competitive as it appears.

Flour and Breakfast Cereals: Market Power with Heterogeneity

The 1970 SIC unfortunately lumps together the technically and economically dissimilar flour and breakfast cereal industries. Therefore, the internal cost heterogeneity that the data show for this industry may in fact be due to it being split into two parts - a highly profitable, heavily advertised breakfast cereal segment, and a low-profitability flour milling segment. Given the existence of studies which document market power in the breakfast cereals market (Schmalensee, 1978), we will cautiously classify this industry as generating profits due both to internal cost heterogeneity and price-raising market power.

Feed Industry: Workably Competitive

All the indicators point to classifying this technologically fairly simple industry as competitive.

Biscuits: Market Power

This industry earns fairly high profits which are spread relatively evenly over its member firms. It is highly concentrated with not many firms in total, and does some advertising. It seems reasonable to attribute its profitability to the exercise of the price-raising power of its leading firms, probably building on elasticity-reducing brand loyalties.

Bakeries: Workably Competitive with Heterogeneity

Although there is a wide range of profitability in this industry, and although it is naturally protected from competition by the perishability and high transport costs of the product, the very large number of firms and their small average size make it very unlikely that any pure price-raising market power could be sustained, or that sustained cost differentials could be maintained. Thus it seems likely that the most profitable bakeries owe their success to their ability to produce specialty bakery products for which a premium price can be charged.

Confectionery: Market Power with Heterogeneity

This is an unusually profitable industry, but the profits are very unevenly distributed. The most successful firms have profit margins around 50%, and are also relatively large (Column 6).

It is likely that, in this industry as in the others, some internal profit margin heterogeneity is due to differences between firms in their cost performance. But making confectionery is not a very complicated business, and firm sizes are quite small, so it seems most improbable that profitability differences of this magnitude are all, or even mostly, reflections of differences in costs.

Instead, a market power explanation is suggested by the high advertising/sales ratio: nationally marketed brands command a price premium, while other firms must operate on contract or in less profitable niches in the market.

Of course, it can be argued that higher profits are the justified rents earned by those firms which are able to produce a superior and non-imitable product for which consumers are happy to pay a premium (and that advertising expenses are just the necessary costs of letting consumers know about the existence of superior products). This is an important debate, but not one that we can go into further here, given that our focus is on cost performance. In their important study of ther U.S. food manufacturing sector, Connor et al. conclude that "the predominant content of food and tobacco advertising - particularly T.V. advertising - is noninformational" (1985, p.231). If valid, this conclusion would probably apply too to the Canadian food industry.

Cane and Beet Sugar Processors: Workably Competitive

This is an industry with low total profitability, which is spread fairly evenly amongst member firms, and low natural entry barriers. It thus appears to function as a workably competitive industry.

Note, however, the large average size of firm, small number of firms, and high concentration ratio.

In the traditional structure-conduct-performance paradigm, these structural characteristics would be prima facie evidence that the industry is non-competitive. What we seem to have, then, is an example of a 'contestable' industry (see Baumol, 1982) - that is, one in which the threat or actuality of competition from outside the industry is sufficient to prevent even highly concentrated incumbent firms from developing any market power. In this case, the competitive discipline is probably administered by imports - note the high import share (Column 12) and low tariff (Column 10), which is in any case applied to only a small proportion of imports (Column 12, in brackets).

Vegetable Oil Mills: Workably Competitive

This industry works on very low profit margins, and has a very flat cost distribution. The low profit margin is somewhat misleading, since Column 14 reveals that this industry has by far the lowest ratio of value added to total shipments of any food industry (around 11% - the average for the sector as a whole is 32%), so that profits as a proportion of the capital and labour resources committed to the industry are relatively larger than the margin on total value of shipments reveals.

But, given the high import and export shares, it is probably reasonable to place this industry in the 'workably competitive' category.

Soft Drink Manufacturers: Market Power with Heterogeneity

This is a fairly profitable industry with a wide range between the most- and least-successful operators. It produces a highly advertized consumer product in a market segmented into a few major brands (Coca-Cola, Pepsi, 7-Up), and many regional and private-label varieties. Thus, we could conclude that at least some of the profit heterogeneity observed in this industry should be attributed to premium prices charged by the most successful operators.

Distilleries and Breweries: Market Power

Both of these industries are highly profitable, with even 'fringe' firms returning substantial profit margins. They are highly concentrated and protected from competition by an intricate network of barriers to international and interprovincial trade and preferential markups imposed by provincial government-run retailing monopolies. These two important industries provide the clearest example in the food and beverage sector of traditional across-the-board price-raising market power, aided and abetted by government policies.

2.4 Summary

We have examined intra-industry data to ascertain the extent to which differences in profitability across industries can be accounted for by differences in the prevalence of relatively high-profit firms within industries. Then we asked how much of the intra-industry heterogeneity could be ascribed to differences in the market power of particular firms or groups of firms, and how much is due to differences in cost performance.

We found some internal heterogeneity in all sixteen of the food and beverage industries. However, in nine of them, internal profitability performance is spread fairly evenly. Six of these nine (slaughtering and meat processors, poultry processors, dairy products, feed mills, cane and beet sugar processors, and vegetable oil mills) earned low profits overall, and were judged to be workably competitive. The other three (biscuits, distilleries and breweries) have large profit margins which appear to be due to price-raising market power.

Of the seven industries with relatively heterogeneous profit structure, in only one case (fish procssors) did we estimate that the heterogeneity can all be ascribed to intra-industry cost differences. In the other industries studied (fruit and vegetable canners and preservers, frozen fruit and vegetable processors, flour and breakfast cereals, bakeries, confectionery manufacturers and soft drinks), we found evidence that some of the higher profitability of the most successful firms is generated by higher prices rather than lower costs. But the size of the intra-industry differences in profitability are too large to be plausibly all due to price differences. That is, within these seven industries there appears to be substantial variation in the cost efficiency of firms.

3. THE INTRA-INDUSTRY DIMENSIONS OF COST CHANGES, 1970-79

3.1 Introduction

In this chapter, we examine the changes in costs or productivity that occurred within the food and beverage industries over the decade of the 1970s (the period covered by the intra-industry database used in the previous chapter). We will be able to decompose each industry's productivity growth into the contribution made by changes in the cost performance within firms, and changes in the distribution of output between high- and low-productivity firms.

That is, we aim to assess the relative relevance of the standard micro-economic theory of production and the `Industrial Organization' (IO) paradigm to observed productivity growth at the industry level. Production theory attributes all productivity change to things going on inside firms - capital/labour substitution and adoption of new techniques, in particular. The IO approach, in contrast, has typically taken each firm's production technology as given, and examined the changes in industry productivity that can be attributed to changes in the allocation of output across firms, for example as lower-cost new firms enter, or as competitive pressures force relatively high-cost operators to exit from an industry.

By dividing total productivity effects into these two components we can thus examine and quantify the effects of concentration changes on productivity. Although we shall not explicitly measure concentration effects, these will be implicit in the changes in output share distributions. Such information ought to be useful from a policy standpoint since it can be used to identify those industries where changes in firms' output share distributions (concentration) led to improvements in productivity and those for which changes in these distributions led to reductions in productivity. It will also help in showing where productivity improvements were due to firm-specific effects where output shares stayed constant. These results can then be supplemented by or compared with those of Chapter 4 which will yield similar information but from a somewhat different perspective.

3.2 **An Accounting Framework**

In this section, we develop a simple methodology for measuring the kind of effects discussed above. So that we can focus on the intra-industry dimensions of productivity changes, we restrict ourselves to a simpler measure of productivity than will be used in Chapter 4.

We begin by defining productivity of an industry as:

$$A = \frac{X}{I} , \tag{1}$$

where: X is real gross output, and

I is real input (the sum of constant price expenditures on capital, labour, energy and materials).

If there are n firms in the industry,

$$A = \frac{\sum_{i=1}^{n} X_i}{\sum_{i=1}^{n} I_i} = \sum_{i=1}^{n} A_i \cdot S_i , \tag{2}$$

where: $A_i = \frac{X_i}{I_i}$, and

$S_i = \frac{I_i}{\sum_{i=1}^{n} I_i}$ (firm i's share of the industry's total inputs).

Then the change in productivity for this industry is:

$$(3) \qquad \frac{dA}{dt} = \sum_{i=1}^{n}\left[\frac{dA_i}{dt} \cdot S_i + \frac{dS_i}{dt} \cdot A_i \right] ,$$

while the rate of growth of productivity for the industry is:

$$(4) \qquad \dot{A} = \frac{dA}{dt} \cdot A^{-1} = \sum_{i=1}^{n}\left[\dot{A}_i \cdot S_i \cdot \frac{A_i}{A} + \frac{dS_i}{dt} \cdot \frac{A_i}{A} \right] .$$

Equation (4) decomposes an industry's productivity growth into the sum over all firms of:

(a) each firm's productivity growth, weighted by the share of the firm in total industry input use and by its productivity level relative to the industry mean, and

(b) the change in each firm's share of total industry inputs, weighted by its productivity level relative to the mean.

We can rewrite (4) as:

$$(5) \qquad \dot{A} = \sum_{i=1}^{n}[\dot{A}_i \cdot S_i \cdot \frac{A_i}{A}] + \sum_{i=1}^{n}[\frac{dS_i}{dt} \cdot \frac{A_i}{A}] .$$

The first term picks up the contribution to industry productivity growth of changes in the productivity performance of individual firms; the second term measures the shift-in-shares effect - the productivity change resulting from the expansion and contraction of firms with different levels of productivity. In terms of industry level effects it is useful to know which of the two effects is largest, but we can go further, by disaggregating each industry into categories of firms sharing common characteristics. In keeping with the focus on intra-industry profitability differences that was developed in the previous section, we will divide the firms in an industry into five categories using data for the 1970-1979 period. The categories are defined as:

1) firms that were the high-profit half (HP) of their industry in 1970 and are still HP in 1979;
2) firms that were HP in 1970 but which turn up in the low-profit (LP) segment in 1979;
3) firms which are LP in both years;
4) firms which were LP in 1970 but HP in 1979; and
5) firms in the industry in 1970 which exited before 1979, and firms in the industry in 1979 entering after 1970.

For each category j, we can define:

$$\text{(6)} \qquad \mathrm{DPROD}_j = \sum_{i \in n_j} \left[\dot{A}_i \cdot S_i^0 \cdot \frac{A_i^0}{A^0} \right] \text{, and}$$

$$\text{(7)} \qquad \mathrm{DSHARE}_j = \sum_{i \in n_j} \left[\frac{dS_i}{dt} \cdot \frac{A_i^0}{A^0} \right] ,$$

where: n_j is the number of firms in category j (and only these firms are included in the summation), and the superscript "0" represents the base year, 1970.

Expressions (6) and (7) are straightforward enough for categories 1 through 4. For category 5, however, we have the difficulty that rates of change cannot be calculated when firms have zero output in 1970 or 1979. We deal with this by defining:

$$(8) \qquad \text{DPROD}_5 = \left[\frac{(A_5^1 - A_5^0)}{A_5^0}\right] \cdot S_5^0 \cdot \frac{A_5^0}{A^0} \text{, and}$$

$$(9) \qquad \text{DSHARE}_5 = (S_5^1 - S_5^0) \cdot \frac{A_5^0}{A^0} \text{,}$$

where: $A_5^t = \sum_{i \in n_j} \left[\frac{X_5^t}{(\sum_{i=1}^{n} I_i^t)} \right]$,

$S_5^t = \sum_{i \in n_j} \left[\frac{I_5^t}{(\sum_{i=1}^{n} I_i^t)} \right]$,

index '0' refers to the value in 1970, and

index '1' refers to the value in 1979.

Thus, DPROD_5 is the (share-weighted) difference between productivity of entering firms in 1979 and exiting firms in 1970, rather than the change in the productivity of a fixed group of firms, as is measured by the other DPROD terms. Similarly, DSHARE_5 measures the difference between the 1979 input share of firms entering after 1970, and the 1970 input share of firms exiting before 1979 (rather than the change in share of a fixed group of firms).

With the problem of entering and exiting firms dealt with, we have decomposed an industry's total percentage change in productivity
into ten terms:

$$\dot{A} = \sum_{j=1}^{5} \mathrm{DPROD}_j + \sum_{j=1}^{5} \mathrm{DSHARE}_j \,, \tag{10}$$

all of which can be calculated from our intra-industry data.

3.3 Data and Results

3.3.1 Data Definitions

The data used to calculate the DPROD and DSHARE terms are derived as follows:

- gross value of output, and value of materials, energy and labour inputs are from the Census of Manufactures;
- output, materials and energy are deflated by price indexes supplied by the Industry Product Division of Statistics Canada (and used by them in constructing the constant-dollar Input Output Tables);
- wages and salaries (labour input) are deflated by the change in wage and salary payments per employee between 1970 and 1979;
- real end-year capital stock figures are available at the industry level from the Baldwin and Gorecki database. Capital expenditure data are available at the plant level. Therefore, estimates of the real capital stocks of each of our five categories of firms in 1970 and 1979 were obtained by distributing the total industry stock in proportion to each category's share in the total capital expenditures made in its industry.

3.3.2 Results at the Sectoral Level

Table 2 shows the rates of change of productivity (A_i),

Table 2: Changes in Productivity and Levels and Changes in Input Shares, Canadian Food and Beverage Industries; 1979 vs. 1970

Industry (SIC)	RATE OF CHANGE OF PRODUCTIVITY (A_i)					1970 SHARE OF INPUT COSTS (S_i)					CHANGE IN INPUT SHARE (dS_i/dt)				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
1011 Slaughtering and Meat Processors	-0.051	-0.136	-0.074	0.010	-0.091	0.529	0.098	0.217	0.008	0.148	-0.035	0.037	-0.016	-0.001	0.013
1012 Poultry Processors	0.021	-0.007	-0.030	0.062	-0.026	0.179	0.059	0.278	0.092	0.393	0.030	0.011	0.006	0.098	-0.145
1020 Fish Prod. Ind.	-0.021	-0.096	-0.022	0.349	-0.054	0.117	0.348	0.146	0.108	0.281	0.200	-0.027	-0.008	-0.032	-0.133
1031 Fruit & Veg. Canners & Pres.	0.008	-0.222	0.024	0.168	0.014	0.309	0.508	0.229	0.047	0.357	0.020	0.017	0.099	-0.009	-0.127
1032 Frozen Fruit & Veg. Proc.	0.070	-0.020	0.086	0.525	0.182	0.253	0.127	0.349	0.029	0.243	0.073	-0.038	-0.022	-0.016	0.002
1040 Dairy Prod. Ind.	0.068	-0.031	0.052	0.159	0.028	0.373	0.062	0.228	0.036	0.302	0.058	0.023	0.073	0.008	-0.162
1050 Flour & Breakfast Cereal Prod.Ind.	-0.014	-0.146	0.010	0.053	0.027	0.432	0.000	0.049	0.074	0.445	-0.085	-0.000	0.024	0.018	0.079
1060 Feed Industry	0.101	0.048	0.092	0.234	0.134	0.202	0.193	0.172	0.134	0.299	0.062	0.046	-0.014	0.007	-0.102
1071 Biscuits Mfrs.	-0.199	-0.209	-0.048	-0.029	0.019	0.332	0.043	0.383	0.023	0.220	0.070	-0.022	0.114	0.000	-0.163
1072 Bakeries	0.008	-0.087	-0.004	0.097	-0.044	0.274	0.068	0.115	0.108	0.434	0.066	0.088	0.007	0.010	-0.172
1081 Confectionery Mfrs.	0.077	-0.153	-0.073	0.213	0.035	0.333	0.090	0.316	0.034	0.227	-0.051	0.060	-0.018	0.026	-0.016
1083 Veg. Oil Mills	-0.012	-0.036	0.000	0.067	0.006	0.191	0.323	0.000	0.130	0.356	-0.055	-0.164	0.000	0.221	-0.002
1091 Soft Drink Mfrs.	0.052	-0.063	0.061	0.240	0.058	0.078	0.301	0.149	0.085	0.287	0.066	0.022	0.008	0.062	-0.158
1092 Distilleries	0.057	-0.077	0.279	0.444	-0.058	0.332	0.431	0.064	0.155	0.018	-0.039	-0.036	-0.025	0.025	0.075
1093 Breweries	0.081	0.000	-0.032	0.147	-0.056	0.293	0.000	0.036	0.307	0.364	0.109	0.000	0.005	0.092	-0.022

the 1970 share of input costs (S_i), and the change in input shares (dS_i/dt), for each of the five categories. Note that the largest productivity declines are found in category 2 (1970 high-profit firms becoming low-profit in 1979) and the largest increases in category 4 (firms moving into the high-profit 'half' of their industry). This is as expected. The 1970 cost share data show that, on average, firms were more likely to remain in their 1970 profitability class than move. The changes in shares show no particular pattern, except for the difference between exiting and entering shares, on which we will have more to say below.

Rather than analyze Table 2 in detail, we go to Table 3, showing the weighted DPROD and DSHARE terms, which sum, as in equation (10), to the total productivity growth of each industry.

Look first at the 'All Food and Beverages' and 'All Manufacturing' numbers in the bottom two rows. Columns 6 and 12 sum the 'DPROD' and 'DSHARE' terms, respectively, and Column 13 sums both of these, to get the total rate of productivity growth.

Note at once that there was, overall, there was very little total factor productivity growth in the Canadian food and beverages sector between 1970 and 1979 - close to one percent or 0.1 percent per year. That is, a given bundle of capital, labour, energy, and materials produced only one percent more real output in 1979 than in 1970, on average, in this sector. In contrast, a given bundle of inputs was six times more productive in 1979 than in 1970 in manufacturing as a whole (on average). Thus, we see that the productivity performance of the food and beverages sector was relatively poor.

Table 3: Decomposition of Productivity Growth In Canadian Food and Beverage Industries, 1970-79

	CONTRIBUTION OF CHANGES IN PRODUCTIVITY						CONTRIBUTION OF CHANGES IN SHARES									
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Industry (SIC)	DPROD1	DPROD2	DPROD3	DPROD4	DPROD5	SUM DPROD	DSHARE1	DSHARE2	DSHARE3	DSHARE4	DSHARE5	SUM DSHARE	TOTAL CHANGE IN PRODUCTIVITY	OUTPUT SHARE OF EXITS	OUTPUT SHARE OF ENTRANTS	DIFFERENCE BETWEEN 14 & 15
1011 Slaughtering and Meat Processors	-0.027	-0.014	-0.015	0.000	-0.014	-0.070	-0.035	0.038	-0.015	-0.000	0.014	0.002	-0.068	0.148	0.161	0.013
1012 Poultry Processors	0.004	-0.006	-0.008	0.005	-0.010	-0.015	0.032	0.011	0.006	0.093	-0.144	-0.002	-0.017	0.393	0.248	-0.145
1020 Fish Prod. Ind.	-0.003	-0.034	-0.003	0.035	-0.016	-0.021	0.210	-0.028	-0.008	-0.029	-0.136	0.009	-0.011	0.281	0.148	-0.133
1031 Fruit & Veg. Canners & Pres.	0.003	-0.014	0.005	0.007	0.014	0.015	0.021	0.019	0.092	-0.009	-0.125	-0.002	0.013	0.357	0.230	-0.127
1032 Frozen Fruit & Veg. Proc.	0.020	-0.003	0.027	0.013	0.043	0.100	0.082	-0.042	-0.020	-0.013	0.002	0.009	0.109	0.243	0.245	0.002
1040 Dairy Prod. Ind.	0.027	-0.002	0.011	0.005	0.008	0.049	0.060	0.024	0.069	0.007	-0.160	0.002	0.051	0.302	0.140	-0.162
1050 Flour & Breakfast Cereal Prod.Ind.	-0.006	-0.000	0.000	0.004	0.011	0.009	-0.091	-0.000	0.022	-0.017	0.075	-0.011	-0.002	0.445	0.524	0.079
1060 Feed Industry	0.022	0.009	0.015	0.029	0.039	0.114	0.068	0.047	-0.013	0.007	-0.100	0.010	0.124	0.299	0.197	-0.102
1071 Biscuits Mfrs.	-0.081	-0.010	-0.015	-0.001	0.004	-0.104	0.086	-0.023	0.096	-0.000	-0.153	0.008	-0.096	0.220	0.057	-0.163
1072 Bakeries	0.002	-0.006	-0.000	0.010	-0.019	-0.013	0.070	0.091	0.006	0.010	-0.171	0.006	-0.007	0.434	0.262	-0.172
1081 Confectionery Mfrs.	0.030	-0.014	-0.021	0.006	0.007	0.008	-0.059	0.059	-0.016	0.020	-0.015	-0.011	-0.003	0.227	0.211	-0.016
1083 Veg. Oil Mills	-0.002	-0.012	0.0	0.008	-0.002	-0.008	-0.056	-0.166	0.0	0.208	-0.002	-0.016	-0.024	0.356	0.354	-0.002
1091 Soft Drink Mfrs.	0.010	-0.019	0.008	0.018	0.017	0.034	0.071	0.022	0.007	0.056	-0.165	-0.011	0.026	0.287	0.129	-0.158
1092 Distilleries	0.012	-0.036	0.013	0.055	-0.0011	0.043	-0.039	-0.040	-0.019	0.020	0.069	-0.009	0.034	0.018	0.093	0.075
1093 Breweries	0.023	0.0	-0.001	0.045	-0.022	0.045	0.104	0.0	0.004	-0.091	-0.024	-0.007	0.038	0.364	0.342	-0.022
All Food and Beverages	0.002	-0.011	0.001	0.016	0.004	0.012	0.034	0.001	0.014	0.019	-0.069	-0.001	0.011	0.292	0.223	-0.069
All Manufacturing	0.019	-0.016	0.008	0.027	0.018	0.056	0.030	-0.001	-0.005	0.001	-0.022	0.004	0.060	0.292	0.270	-0.022

Variable definitions and sources are given in the text.

That productivity growth which did occur was generated within categories of firms rather than from shifts of inputs between categories (Columns 6 and 12). Indeed, shifts between categories actually had a very small negative effect on food and beverage productivity growth, though not for all manufacturing (Column 12).

Looking at the contributions made to productivity growth by the five categories of firms (Columns 1 through 5), we see that only the group of firms which slipped from the `high-profit' to the `low-profit' half of their industry had, not surprisingly, negative productivity growth (Column 2), in both the food and beverage sector and in all manufacturing.

Although the net effect of changes in input shares is very small (Column 12), this is made up of some large numbers. For the food and beverage sector, $DSHARE_1$, $DSHARE_3$ and $DSHARE_4$ are all positive and quite large, whereas $DSHARE_5$ is very large and negative. However, these figures do not in fact have much significance for productivity performance. Note from the definition of $DSHARE_j$ (Equation (7)) that a non-zero value will turn up for any category which shows a change in its market share within its industry. The key consideration is whether positive and negative share changes are systematically associated with higher or lower initial levels of productivity, relative to the industry mean ($\frac{A^0_i}{A^0}$ in Equation (7)).

If, for example, growing firms tend to have relatively high productivity in 1970, and declining firms relatively low productivity, their net effect (Column 12) on productivity growth will be positive. But the fact that the net effect is in fact about zero tells us that there is no systematic difference in the initial productivity levels of expanding and contracting firms. What has, overall, happened in the food and beverage sector from 1970 to 1979 is, first, that the output of exiting firms was not fully replaced by output from new entrants, so that the share of the market taken by firms surviving through the decade necessarily increased, and, second, firms exiting after 1970 did not, in 1970, have lower productivity than the average for their industry. This may be because 'exit' can take the form of sale of a plant to another firm as a going concern, as well as the scrapping of plants.

The actual (output) shares of exits and entrants are shown in Columns 14 and 15, and the difference between them in Column 16. Whereas about 29 percent of the 1970 output of the food and beverage sector was produced by firms exiting from the sector before 1979, only 22 percent of 1979 output came from entrants building new plants or acquiring existing operations. For manufacturing as a whole the picture is qualitatively similar but the difference in output shares is smaller - just over 2 percentage points (Column 16). In all manufacturing, as in food and beverages, though, the net effect of shifts in shares on productivity growth (Column 12) is negligible, implying again that exiting firms cannot be systematically distinguished from survivors by their productivity in 1970.

In summary, we find (a) that there was only a small amount of total factor productivity growth in the food and beverage sector over the 1970's, and (b) that all of the growth that did occur was due, on average, to productivity changes occurring within the five categories of firms into which each industry is disaggregated.

The next stage of our investigation is to see whether these conclusions hold up when we look below the sector level to examine the productivity performance of fifteen[3] 4-digit SIC food and beverage industries.

3.3.3 Results for Individual Industries

The close-to-zero average growth in productivity of the food sector conceals substantial variations in productivity performance at the individual industry level. From Column 13 of Table 3 we can see that there was a spread of more than twenty points in 1971-79 factor productivity growth rates - from the more than twelve percent increase turned in by the feed industry to the nearly ten percent decline in productivity observed in the biscuits industry. Overall productivity increased in seven industries, and declined in eight.

In general, the decomposition of productivity change at the industry level is consistent with the sector-level finding that it is changes in productivity within groups, rather than shifts in output between them, that accounts for the bulk of the productivity change.

We can focus, then, on columns one through five, looking in particular for explanations of the performance of the extreme industries. In the cases of Slaughtering and Meat Processors, Frozen Fruit and Vegetable Processors, Dairy Products and Feed Industry (all of which showed changes in productivity larger than ± 5 percent) productivity performance is spread fairly evenly across all or most of the sub-categories of firms. This can be explained either as the result of industry-wide technical change increasing (or decreasing) the productivity of all plants, or as due to measurement error, most likely in one of both of the industry-level output and input price deflators. An error in a price deflator would bias the results for all of the categories of firms within an industry.

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[3] One fewer than the sixteen industries analyzed in Chapter 2 because cane and beet sugar processors (SIC 1082) has too few plants for the disaggregated intra-industry analysis to be possible, given Statistics Canada confidentiality restrictions.

The biscuit industry (SIC 1071) displayed the large fall in factor productivity, which is almost entirely attributable to a sharp decline in the performance of the best firms (Column 1). At this level of disaggregation it is possible that the event was due to one or two large firms happening to have particularly good years in 1971), or bad years in 1979. However, the confidentiality restrictions on the use of the database prevent us from investigating the matter.

In summary, there is a wide dispersion - perhaps suspiciously wide - in the productivity growth performance of three and four-digit SIC food industries. The results depend heavily on the price deflators used to convert current-dollar output and inputs to constant-dollar quantities. These deflators are unpublished and it is probably fair to be cautious of their accuracy at such a disaggregated level. The individual-industry numbers should probably be carefully checked on a case-by-case basis.

However, the data do support a model in which productivity growth is something that is spread across the firms in an industry, rather than due to shifts in output shares between high and low-productivity firms. This finding justifies the use, in the next chapter, of industry aggregate data to estimate a model which is different from that used above and provides an alternative measure of productivity with which to compare the results of this chapter.

4. CONCENTRATION AND COSTS: INDUSTRY-LEVEL ANALYSIS

4.1 Introduction

The two previous chapters of this paper have provided a wide array of information on both intra-industry (i.e., inter-firm differences within each industry) and to some extent to these and other factors have been compared across industries. In this chapter, we shall extend both aspects further, but this time using only industry-level data. In particular, we will measure the extent to which the distribution of firm's market shares (i.e., concentration) and changes in these distributions have affected industry average costs of production, or productivity, for 17 food and beverage industries over the period 1961-1982.

We choose this as our third and final topic for a number of reasons. First, it is well known that society views high concentration with concern - the continued existence and application of competition policy around the world is evidence of this. It is also an accepted fact that in most industries as concentration rises, the likelihood of profits increasing, particularly for the 'dominant' firms, is high. The main thrust of economic analysis of this phenomenon has been to attribute the profits of high-concentration industries to collusion and price-fixing. Competition policy and legislation has in the past been formulated largely to prevent such activities and therefore has discouraged increases in concentration, mostly in high-concentration industries.

As noted in Chapter 2, the collusion or 'mainline' view of industrial organization - which has previously provided the main justification for competition policy action - has been under attack for some time. Criticism of the mainline approach has been based on the argument that the commonly observed link between higher profits and higher concentration levels is due to the propensity of more efficient (usually larger) firms to attain greater market shares and therefore earn greater profits due to their competitive 'edge'. This 'alternative', or 'efficiency', view is well-documented in Green (1987), who in fact questions the relevance of concentration policy, given what he accepts as widespread evidence in favour of the efficiency view. This evidence, he believes, severely undermines the 'mainline' case, since even if collusion is taking place in an industry, if firms dominating that industry are also more efficient, these efficiency gains may outweigh the losses due to price-fixing[4]. Such theories are only valid, however, if we have facts to back them up with - and facts in either direction are sparse - both regarding evidence of collusion and efficiency - particularly for the Canadian food and beverage industries. Although Lopez (1984) has found some evidence of collusion for the food and beverage sector in Canada (i.e., at the two-digit level of aggregation), there is no information at all regarding the existence and size of any relationship between concentration and costs for this group of industries. Clearly, such information would be useful to establish a case for or against policy action in food processing from an efficiency viewpoint.[5] Evidence obtained from the model developed would also help by assessing the validity of the 'alternative' view and add some substance to what has largely been a non-empirical debate. This would also have direct relevance to mergers in high-concentration industries where applicability of the efficiency defence (Section 68(1) of the relatively new Competition Act (Canada (1986)) in a case where a Competition Tribunal might otherwise block the merger. If we can show how increases in concentration through merger might affect costs in the high-concentration industries studied, we will reduce some uncertainty about the circumstances under which such a defence might be appropriate and can be substantiated by fact. Hopefully, our results will contribute to a clearer understanding of the extent to which such claimed efficiencies exist, both by illustrating the practicality of our method (indicating possible usefulness for other industries than food processing) and by providing some tangible evidence on a subject which so far has rarely been approached directly (i.e. by a direct measurement of the effects of concentration changes on costs of production).[6]

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[4] Even if such efficiency gains do offset losses from collusion, this will usually only hold if we view cost-savings and wealth transfers as having equal weight per dollar. Wealth distribution issues play a potentially important role here; equal weighting of the two effects is perhaps too simplistic an approach to take if it is acknowledged that different individuals will tend to have different marginal utilities of income.

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[5] A more complete analysis would include a test for and measurement of collusion, but we focus on efficiency here since it would seem to be the issue which most needs quantification.

[6] As White(1987) observes, "[e]fficiencies are easy to promise, yet may be difficult to deliver. All merger proposals will promise theoretical savings in overhead expense, inventory costs and so on ... on the other hand, diseconomies of scale caused by managerial limitations may also be present" (p. 18). Difficulties

4.2 A Modelling Framework

To implement our test of concentration-cost effects we first considered existing models to see whether these might be useful for our purposes. Previous studies, such as Peltzman (1977), Lustgarten (1979) and Gisser (1982, 1984)[7] have employed models which use endpoint data for two periods (say 1962 and 1982) and which compare rates of change in total factor productivity (TFP) with rates of change in concentration over large numbers of industries.

Aside from the fact that these previous approaches use TFP indexes and therefore impose a priori assumptions about production technology in the industries studied, these methods are oriented to giving a 'snapshot' comparison between two periods, meaning that they can tell us very little about how things have changed over time. If we wish to measure the effects of concentration on costs, it is

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6(cont'd) in quantifying potential efficiencies have also been cited by Kwoka and Warren-Boulten (1986) who observe that "these difficulties might be alleviated by a [merger] policy requiring explicit consideration of a wider range of alternatives short of merger to achieve particular efficiencies" (p. 8). Regarding such alternatives, they note that merging firms "have not always be diligent in seeking out alternative forms of achieving efficiencies and furthermore, have often overestimated the benefits of complete merger" (ibid., p. 12). A conclusion to the efficiency debate is not likely to be established here, however, if only because we limit ourselves to the measurement of production cost effects. Although Kwoka and Warren-Boulton note that "conventional plant-level economies are least likely to be affected by merger" (ibid., p. 3) and that the non-production areas (marketing, distribution, etc.) **may** be where efficiencies through merger might occur, we believe that effects on costs of production are equally relevant and ought not to be ignored.

[7] These four are the only studies which measure efficiency effects directly, rather than through inference (i.e., relating market shares to profits), to our knowledge.

important to know how such effects have taken place and to adopt a model which beforehand assumes as little as possible about the nature of the relationship being studied. The failure of previous approaches to fulfill these as the basic requirements suggested to us that an alternative method which would meet them ought to be formulated.[8]

One approach which satisfies the requirements noted above is applied duality, a popular method of obtaining information about the way in which firms and industries produce when minimizing costs (or maximizing profits). The variety of results (such as input demand elasticities and returns to scale effects) provided by dual flexible forms is a particularly attractive feature in a case such as this, since we would not only like to determine the nature of any relationship between concentration and costs but also any links between concentration and choice of technology, inputs chosen, and so on.

The effects of concentration on costs can be quite readily formulated in a dual framework. If we consider an industry, r, which faces an exogenously determined concentration level h_{rt} and an output level Q_{rt} at time t, it must minimize costs of producing Q_{rt} input prices (which are also exogenously determined)[9]. This behaviour can be expressed using a dual cost function which is relevant over the range of industries, input prices, output and concentration levels prevailing for the sample of industries studied, or:

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[8] Additional discussion regarding the 'alternative' empirical literature can be found in Cahill (1986).

[9] We treat both concentration and output as exogenous variables to make the analysis simple. We don't test for endogeneity but a useful extension would involve relaxation of these assumptions.

$$(11) \qquad C_r(w_{rt},Q_{rt},h_{rt},t) = \min_{X_{rt}} \left(w_{rt}X_{rt} \; : \; f_r(X_{rt}) \geq Q_{rt} \; ; \; h_{rt} \right)$$

where: $f_r(\cdot)$ is a quasi-concave production function which characterizes the technology used by industry r, and to which $C_r(\cdot)$ is dual,

w_{rt} is an 1xn vector of (exogenous) input prices facing industry r at time t,

Q_{rt} is (exogenous) industry output in t $\equiv \sum_{f=1}^{F_{rt}} q_{frt}$,

h_{rt} is the (exogenous) value of the Herfindahl index of industrial concentration[10] in time t for industry r $= \sum_{f=1}^{F_{rt}} \left(\frac{q_{frt}}{Q_{rt}}\right)^2$,

F_{rt} is the number of firms in industry r at time t,

q_{frt} is the output of firm f in industry r during t,

t is a time index (t=1,2,3,...,T) where T is the number of periods being studied, and

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[10] The Herfindahl index (h-index) has become in many regards the preferred measure of industrial concentration relative to the four-firm concentration ratio (CR_4) in much of the recent industrial organization literature on price-cost margins (Waterson 1984, pp. 171-172). Thus, by using the h-index, we ensure consistency between the price-cost margin (market power) approach and that taken here in terms of the concentration measure used. In addition, Sleuwagen and Dehandschuter (1986) find the h-index superior to the CR_4 in identifying market power in high-concentration industries (pp. 201-202). Finally, there is a practical reason for choosing the h-index over the CR_4 - confidentiality rules often forbid the publication of CR_4 data for high-concentration industries, whereas due to the design of the h-index, confidentiality is rarely an issue.

X_{rt} is an nx1 vector of (endogenous) input quantities chosen by industry r at time t.

To ensure duality between $C_r(\cdot)$ and $f_r(\cdot)$ we assume that $C_r(\cdot)$ is non-negative in w_{rt} and Q_{rt}, linearly homogenous in w_{rt}, concave in w_{rt} and continuous (Diewert 1982, pp. 553-554).

To allow for a comparison of changes in costs between different industries (and therefore concentration levels) and changes in these costs over time we must focus on average costs of production, or unit costs. Thus, where production may increase more rapidly in some industries than others, so will total costs - we ought to hold output 'constant' in our comparison of costs between industries. To achieve this equal footing, we compensate for output in the derivation andevaluation of results from our model, but use a total cost function in our estimating procedure. It is simply more convenient to measure total costs since we can borrow a number of comparative static expressions directly from the literature - all results can be readily converted to reflect average effects and are sometimes equivalent in both cases.

4.3 Data Description

Since the sample available to us largely determines the format the empirical model takes, it is useful to briefly outline the nature of the data, before establishing the stochastic version.

The data series covers 17 '4-digit' food processing industries for the period 1961-1982. Both total cost and input cost and price data for capital, production labour, non-production labour, energy, materials are available, as well as output Herfindahl and technology index series. Sample averages are provided in Table 4 for each industry ordered by S.I.C. and industry index number.

As can be seen, there have been some quite significant differences between industries with regards to concentration levels. Input cost shares have also varied considerably across industries with some much more capital-intensive than others (compare poultry processors with breweries). Similarities also exist. Not surprisingly, materials account for the lion's share of costs in all cases - even though average levels vary greatly, ranging from 55 to 90 percent of total costs. And energy, interestingly, appears to have been a relatively unimportant input in the production process in all industries.

More detail about the database used can be found in Appendix 1.

4.4 An Empirical Model

There are a number of flexible functional forms which could be used to estimate (11), but there is little guidance with respect to best choice between these, given an ex ante sample and problem. Evidence from Wales (1977) and Guilkey, Lovell and Sickles (1983) indicates some justification for using the translog (TL) over other forms, however, and given the widely successful application of this form elsewhere we adopt it here.

Table 4. Average Cost Shares and Herfindahl Indices, Canadian Food and Beverage Industries, 1961-1982

			Cost Shares					
Industry Name	Index Number[1]	S.I.C.[2]	capital	prod'n labour	non-prod'n labour	energy	materials	Herfindahl[3] Index
slaughtering and meat processors	1	1011	.026	.067	.029	.006	.873	10.4
poultry processors	2	1012	.019	.089	.023	.009	.860	4.5
fish processors	3	102	.053	.127	.036	.013	.772	6.2
fruit & vegetable processors	4	103	.067	.101	.054	.014	.763	4.5
dairy products	5	104	.039	.050	.062	.014	.834	3.6
flour and breakfast cereals	6	105	.072	.062	.038	.008	.820	13.6
feed mills	7	106	.039	.039	.033	.011	.877	2.8
biscuits	8	1071	.080	.162	.089	.010	.657	17.1
bakeries	9	1072	.075	.167	.129	.023	.605	3.5
confectionery	10	1081	.084	.140	.074	.010	.693	8.9
cane and beet sugar processors	11	1082	.084	.065	.031	.020	.800	22.2
vegetable oil mills	12	1083	.047	.023	.014	.013	.903	20.3
miscellaneous processors n.e.s.	13	1089	.059	.071	.065	.013	.791	5.0
soft drinks	14	1091	.112	.083	.144	.017	.644	8.2
distilleries	15	1092	.176	.089	.086	.023	.626	25.0
breweries	16	1093	.194	.131	.112	.017	.547	30.7
wineries	17	1094	.142	.082	.083	.010	.683	15.7
average (all industries)	-	-	.080	.091	.065	.014	.749	11.9

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[1] These are the numbers used to identify each industry in the notation used for the cost and share equations (14) and (13) and in the comparative static expressions derived from these.

[2] Standard Industrial Classification number (1970 definition) used by Statistics Canada to identify each industry at its level of aggregation (in this case, 4-digit).

[3] The actual concentration data are multiplied by 100 for display purposes. Note that the Herfindahl index is normally bounded by 0 (perfect competition) and 1 (pure monopoly); in this table the equivalent range is 0 to 100. Also note that these data are actually scaled to 1971=1 (like the price, cost and output data) in estimation, but are given in 'raw' form here for more ready comparison with data for other manufacturing industries.

4.4.1 A Translog Model of Concentration - Cost Effects: Estimation and Specification Issues

In order to measure the effects of changes in concentration on changes in costs, we adapt a general TL total cost function specification (i.e., the non-homothetic form with technical change such as that used by Diewert and Wales (1985, p. 5)). To do this, in this analysis we maintain the assumption that the TL is a second-order Taylor's series (exact) approximation about a point. The assumption of exactness is important since if third and higher order terms are not ruled out, econometric complications (non-randomness of the error structure) make estimation difficult, if not impossible.

Aside from introducing concentration effects into the TL specification, the cross-sectional time series sample requires that we also be specific about the way in which such analysis is to be done econometrically. We would have at least three general options to choose from in the construction of a stochastic model. First, we could estimate a separate TL cost function for each industry, showing how concentration changes for each industry differ by comparing results for the 17 industries to be analyzed. This approach would have a maintained assumption that all 17 industries have distinct and dissimilar production technologies. The time-series available for each industry are too short to do this, however.

A second approach would be to pool the sample, treating each industry as if it had exactly the same technology as the other. This is the implicit assumption underlying 2-digit aggregate analyses, but in this sample, aggregation over industries would not be necessary; the data could be 'pooled' and thus all 17 time-series could be added together, perhaps allowing only for concentration effects to differ by industry.

The final option, which we adopt, is to choose a middle ground between the above two extremes and to assume that some similarities in technologies exist, but that all 17 industries, for the most part, have different technologies. This allows us to exploit the larger sample properties obtained by 'pooling', but by imposing the more relaxed assumption that all 17 food and beverage industries have some common features in the production technologies they employ, and some dissimilar features. Unfortunately, we cannot test for the least restrictive first option due to data limitations, but we can test for the second, thus showing whether 2-digit analysis is likely to be valid for our sample.

Fuss (1977) provides a useful discussion of how best to implement the strategy noted above. Although Fuss's approach is used for regional variations in all-of-manufacturing technologies, the technique he uses carries over analogously to the problem being confronted here. He notes that "one approach is to assume that differences in technologies (resulting from [industry] variation) imply that the parameters of the cost function ... are [industry] - specific. In order to conserve degrees of freedom, we would need to restrict [industry] parameter variation to the constant and linear terms of the second-order expansions" (Fuss 1977, p. 98). This technique is adopted here.[11]

An additional feature of our estimation procedure is that we chose to estimate the cost function as a system with the n-1 factor share equations (see below). This is because systems estimation has been shown to be more efficient, thus improving the accuracy of any hypothesis tests performed with the model.

The systems procedure most commonly used is Zellner's iterative method of solving systems of seemingly unrelated regressions (SUR's), Zellner (1962) has shown that his iterative SUR's method is maximum likelihood so long as the system converges. Moreover, it has been shown that this result holds whichever share equation is dropped from the system and that the parameters generated from any one of the possible systems will be equally efficient and of the same magnitude[12]. Hence, Zellner's method will be applied to equations with the properties suggested by Fuss's first method discussed above. Although this does not allow for covariance of cross-industry disturbances in estimation, cross-sectional variations will be accounted for by the explicit use of different first-order parameters for each industry and by evaluating the summary measures at each industry's sample means.

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[11] Fuss discusses two other pooling techniques - Covariance and error components. Neither of these are appropriate here since both assume that observed differences in production technologies are random. We believe, however, that there are likely to be substantial non-random (deterministic) differences between industries and that we should allow and test for these.

[12] Since the factor cost shares sum to one, singularity of the covariance matrix would occur unless one of the share equations were dropped. Barten (1969, pp. 25-27) has shown that when errors are serially independent (as assumed here), it is irrelevant which share equation is deleted from the system under maximum likelihood estimation. Zellner's iterative method is maximum likelihood so long as convergence is reached; it follow's then, that Barten's result will carry over to iterative Zellner estimation providing the system converges.

Given the above considerations, we specify the adapted Translog cost function as:

$$
\begin{aligned}
(12) \qquad lnC(w,Q,h,t) = {} & \sum_{i=1}^{17} \alpha_{0r} + \sum_{i=1}^{5}\sum_{r=1}^{17} \alpha_{ir} lnw_i + \sum_{r=1}^{17} \alpha_{qr} lnQ + \\
& \sum_{r=1}^{17} \alpha_{hr} lnh + \sum_{r=1}^{17} \alpha_{tr} \cdot t + 1/2 \sum_{i=1}^{5}\sum_{j=1}^{5} \beta_{ij} lnw_i lnw_j + \\
& \sum_{i=1}^{5} \beta_{iq} lnw_i lnQ + \sum_{i=1}^{5} \beta_{ih} lnw_i lnh + \sum_{i=1}^{5} \beta_{it} lnw_i \cdot t + \\
& 1/2\beta_{qq}(lnQ)^2 + \beta_{qh} lnQ lnh + \beta_{qt} lnQ \cdot t + \\
& 1/2\beta_{hh}(lnh)^2 + \beta_{ht} lnh \cdot t + 1/2\beta_{tt} \cdot t^2 + e_{irt} ,
\end{aligned}
$$

where: r is the industry index number,

$W_1 = W_k$ (the price of capital inputs),

$W_2 = W_{lp}$ (the price of production labour inputs),

$W_3 = W_{lnp}$ (the price of non-production labour inputs),

$W_4 = W_e$ (the price of energy inputs),

$W_5 = W_m$ (the price of materials inputs),

Q is an index of gross output,

h is the Herfiendahl index,

t is the technology index (time)[13],

---

[13] Notice that this variable, unlike the others in the cost function, is not expressed in logarithms. This distinction is often made in the duality literature (see, for example, Diewert and Wales (1985, p. 5)). Watts and Quiggin (1984) show that, unlike other variables, t should not be expressed in logarithms but as specified here, since a logarithmic variable can lead to parameters which are not invariant to the starting point chosen for t. We set t=1 for 1961 (the first observation for each industry), and increase it by increments for each year thereafter ending with 22 for each industry.

α_{0r}, α_{ir} (i = 1,2,3,4,5), α_{qr}, α_{hr}, and α_{tr} apply to industry r and are zero otherwise, and

e_{irt} is an (independently) normally distributed error term - see more on its properties below.

To keep the notation simple in (12), the total cost, price, output and concentration variables have not been subscripted with r (for industry) and t (for time period) but these do vary over r and t (with the exception of w_k which is the same for all industries - see Appendix 1).

As noted above, (12) is estimated most efficiently as a system with the input cost shares. The optimal factor shares may be derived by applying Shephard's Lemma to (12), viz[14]:

$$(13) \qquad S_i(w,Q,h,t) = \sum_{l=1}^{17} \alpha_{lr} + \sum_{j=1}^{5} \beta_{ij} \ln w_j + \beta_{iQ} \ln Q + \beta_{ih} \ln h + \beta_{it} \cdot t + e_{irt} \ ; \quad i = 2,3,4,5.$$

The singularity of the covariance matrix of the share equations is avoided by dropping the capital share. Any of the other four factor shares could have been chosen instead; as metioned already, it is immaterial which is dropped so long as the system iterates to convergence.

With regards to the disturbance (error) terms appended to each equation (e_{irt}; i = 2,3,4,5), these are assumed to have the following properties:

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[14] Since the translog is in logarithms, differentiation with respect to $\ln w_i$ yields the factor shares instead of factor demands.

$$\text{(i) } E(e_{irt}) = 0 \; ; \; i = 1,2,\ldots,5 \; ; \; r = 1,2,\ldots,17 \text{ , and}$$

$$\begin{aligned} \text{(ii) } E(e_{irt}\, e_{jsu}) &= \sigma^2_{ij} \text{ for } r = s,\ t = u \\ &= 0 \text{ for } r \neq s,\ t \neq u \text{ ,} \end{aligned}$$

where: σ^2_{ij} is the variance of the estimator.

Thus, the error terms are assumed to have the usual properties (i) of zero mean and (ii) constant variance (i.e., homoscedasticity). In addition the error terms are assumed to be contemporaneously correlated (i.e., correlated across equations - this is the assumption underlying SUR's) but not across industries or time periods (i.e., they are temporally and cross-sectionally independent). Thus, (ii) implies that there is correlation across equations, but only within industries and time periods.

To ensure that the regularity conditions (specifically, linear homogeneity in w for C; homogeneity of degree zero in w for S_i) are met, we shall impose them in estimation, rather than testing them. In particular, estimation is done with the following first-order restrictions imposed:

$$\sum_{i=1}^{5} \alpha_{ir} = 0 \; ; \; r = 1,2,\ldots,17 \text{ ,}$$

i.e., there is one restriction for each industry, a total of 17 in all. Since the four sets of second-order cross-price coefficients are common to all industries, there are eight more of these[15]:

$$\sum_{j=1}^{5} \beta_{ij} = 0 \ \forall i \ ; \ \sum_{i=1}^{5} \beta_{iq} = 0 \ ; \ \sum_{i=1}^{5} \beta_{ih} = 0 \ ; \ \sum_{i=1}^{5} \beta_{ih} = 0$$

Moreover, since the coefficients in share equations (13) must conform to those in the cost function (12), there are a number of cross-equation restrictions which must be imposed. The 17 intercept terms in each of the 4 share equations must be forced to equal the 17 respective first-order coefficients for each of the 4 relevant prices in the cost function (a total of 72 restrictions); the five price coefficients in each share equation must be forced to equal their counterparts in the cost function (a total of 20 restrictions); finally, the output, concentration and trend coefficients in the shares must equal those in the cost function (another 12 restrictions). In total, with homogeneity and cross-equation restrictions, there are 128 restrictions which must be imposed in estimation.[16]

In addition to the fact that the model is being applied to a particularly large sample (374 observations), these restrictions mean that estimation of the system (12) and (13) has high random memory requirements in the computation of parameters.

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[15] Note that the first restriction in this group assumes symmetry, or Young's theorem ($\beta_{ij} = \beta_{ji}$) applies.
Symmetry is required under cost minimization.

[16] Ideally the unrestricted estimated parameters would satisfy these conditions, but this is rarely the case in applied duality, and so we decided to impose them from the outset. There is some evidence to suggest that the imposition of constraints under estimation may artificially boost the likelihood value of the system (Levy (1988)). In spite of this potential bias, the constraints were imposed largely due to time and computer resource limitations as a second best to exhaustive statistical tests of these conditions.

4.4.2 Specification Tests: Refining the Model

Before drawing inferences from a general model such as (12) and (13), it is important to establish whether a more restrictive specification is better. For example, we might find that concentration effects do not vary across industries at all, or that all industries have the same production technology. Under such circumstances, it would be wrong to draw inferences from a model which assumes such differences exist.

There is a much larger selection of possible specification restrictions - beyond those regularity conditions noted above - which might be tested with (12) and equations (13). We limited our tests to three categories:

(i) restrictions across industries;
(ii) restrictions to determine production structure (e.g. homotheticity or homogeneity and the existence of technical change); and
(iii) restrictions to determine how concentration affects costs (e.g., whether it has an effect on choice of inputs).

The hypotheses which fall into category (iii) are arguably the most important given our interests here; hypotheses (i) are probably of least interest. With this priorization in mind, hypothesis testing will be conducted primarily on these grounds.

We used the Wald and LR hypothesis test procedures (see Harvey (1981), p. 75) to determine the validity of a large selection homothetic and homogeneous technology models - including those implied by a Cobb-Douglas production function - but rejected most of these. We also rejected the hypothesis (with almost 100% confidence) that concentration changes had had no effect of costs of production in the industries studied - the significant role of concentration suggests that the model would have been misspecified had the variable been excluded.

There were a number of restrictions, however, which we could not reject and these were:

(a) $\alpha_{0r} = \alpha_0 \;\forall\; r$ (cost function intercept terms are the same for all 17 industries),

(b) $\alpha_{tr} = \alpha_t \;\forall\; r$ (neutral technical change of the same magnitude for all industries), and

(c) $\alpha_{hr} = \alpha_{hh1} \;\forall\; r\colon \bar{h}_r \geq 10$ (first-order concentration effects the same for 'high-concentration' industries - those with average Herfindahl indexes greater or equal to 10).

In addition to restrictions (a), (b) and (c), we impose the restriction that $\beta_{ht} = \beta_{qt} = \beta_{tt} = 0$ on (12) to arrive at our final model. This latter group of constraints is imposed on the basis of evidence from Denny, Fuss and Waverman (1979, p. 71) who found that inclusion of non-price technical change cross effects prevented convergence of their model. The loss of information involved in doing this is thought to be minor.

The final specification chosen for estimation of the cost/share system is:

$$
\begin{aligned}
(14) \qquad lnC(w,Q,h,t) = {} & \alpha_0 + \sum_{i=1}^{5}\sum_{r=1}^{17} \alpha_{ir} ln w_i + \sum_{r=1}^{17} \alpha_{qr} lnQ + \\
& \sum_{r \in Lh} \alpha_{hr} ln h + \alpha_{hh1} ln h + \alpha_t \cdot t + 1/2 \sum_{i=1}^{5}\sum_{j=1}^{5} \beta_{ij} ln w_i ln w_j + \\
& \sum_{i=1}^{5} \beta_{iq} ln w_i lnQ + \sum_{i=1}^{5} \beta_{ih} ln w_i ln h + \sum_{i=1}^{5} \beta_{it} ln w_i \cdot t + \\
& 1/2 \beta_{qq} (lnQ)^2 + \beta_{qh} lnQ ln h + 1/2 \beta_{hh} (ln h)^2 + e_{irt} \ ,
\end{aligned}
$$

where: $Lh = r$: average $h < 10$, and

$$\alpha_{hhi} = D_r \cdot \alpha_{hhi} : D_r = 0 \ \forall \ r \in Lh \ ; \ D_r = 1 \ \forall \ r \notin Lh.$$

The above specification, as can be seen, incorporates the restrictions on α_{0r}, α_{tr}, and α_{hr} (see (12) for the unrestricted version) suggested by (a), (b) and (c) above. The cost function (14) was estimated as a system with equations (13), with the regularity restrictions imposed, and converged after 10 iterations.[17]

To ensure efficiency of specification, a number of the tests from the previous section were performed again, using the Wald method.[18] In all cases, we rejected more restrictive versions, thus showing generally that concentration had a statistically significant effect on costs during the period studied. Also, technical change took place (i.e., we rejected the null hypothesis of no technical change).

Given the outcome of these tests, we conclude that the cost function specification (14) is correct for our purposes and we can treat the parameter estimates as efficient and unbiased within the context of the tests chosen.

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[17] The convergence limit chosen allowed a maximum of 0.1 percent change in the magnitude of estimated coefficients from iteration to iteration.

[18] For details, See Cahill (1986)

4.5 Econometric Results

4.5.1 Parameter Estimates and Model Fit/Performance

The final estimated coefficients of (14) and share equations (13), then, are presented in Tables 5 to 9. As can be seen, most variables are highly significant on the basis of their t-ratios (the critical value t(95%), assuming asymptotic properties is 1.96). The exceptions are: the intercept term α_0; the first-order concentration effects α_{h3}, α_{h4} , α_{h5} , α_{h7} , α_{h9} , α_{h10} , α_{h14} (for the fish products, fruit and vegetable, dairy products, feed, bakeries, confectionery and soft drink industries industries); the second-order concentration term β_{hh} ; and some of the cross price coefficients: β_{12}, β_{24} , β_{33} and β_{34} . Finally, the parameter α_t, which measures neutral technical change is also insignificantly different from zero.

Additional considerations with regards to the estimates (other than t-ratio values on the estimated parameters) include goodness of fit and behaviour of residuals (i.e., whether they fit the characteristics assumed for e_{1t}, e_{2t} ... e_{5t} in Section 4.4.1). The only measure we have of goodness of fit is the R^2 value of each equation of the system. These statistics are high by usual standards (an R^2 of 1.0 indicates perfect fit) but because of the nature of systems estimation, these are less reliable indicator than the R^2's under the OLS case.

In order to determine whether the estimated residuals were 'normal' in behaviour, we inspected plots of the residuals about zero (see Cahill (1986, Appendix 3)). These, along with tests for skewness

Table 5. Total Cost Function Estimated Coefficients and Summary Statistics, Final Model, Canadian Food and Beverage Industries, 1961-1982[1]

Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio
α_{0}	0.017	0.8	α_{24}	0.117	34.5	α_{38}	0.098	37.5
α_{11}	0.033	9.0	α_{25}	0.066	20.1	α_{39}	0.136	49.2
α_{12}	0.031	8.8	α_{26}	0.083	24.1	α_{310}	0.084	30.2
α_{13}	0.060	18.4	α_{27}	0.057	17.2	α_{311}	0.041	14.6
α_{14}	0.070	19.5	α_{28}	0.179	56.7	α_{312}	0.024	8.3
α_{15}	0.046	13.2	α_{29}	0.182	56.9	α_{313}	0.075	27.4
α_{16}	0.080	21.5	α_{210}	0.158	45.3	α_{314}	0.153	53.8
α_{17}	0.050	14.2	α_{211}	0.088	24.7	α_{315}	0.094	33.8
α_{18}	0.087	25.6	α_{212}	0.041	12.8	α_{316}	0.122	44.8
α_{19}	0.082	23.1	α_{213}	0.090	26.9	α_{317}	0.089	29.4
α_{110}	0.091	25.0	α_{214}	0.090	28.9	α_{41}	0.003	3.6
α_{111}	0.092	25.2	α_{215}	0.105	30.5	α_{42}	0.007	8.6
α_{112}	0.058	16.1	α_{216}	0.151	43.3	α_{43}	0.010	14.5
α_{113}	0.066	18.6	α_{217}	0.088	24.8	α_{44}	0.010	12.8
α_{114}	0.101	27.1	α_{31}	0.036	13.0	α_{45}	0.011	14.4
α_{115}	0.160	43.8	α_{32}	0.028	10.0	α_{46}	0.006	8.0
α_{116}	0.176	48.1	α_{33}	0.043	17.0	α_{47}	0.009	12.1
α_{117}	0.122	31.0	α_{34}	0.062	22.8	α_{48}	0.008	11.1
α_{21}	0.085	25.1	α_{35}	0.070	25.6	α_{49}	0.020	26.5
α_{22}	0.108	32.4	α_{36}	0.048	17.1	α_{410}	0.008	10.6
α_{23}	0.140	46.8	α_{37}	0.041	14.7	α_{411}	0.017	22.2

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[1] The final model is the system of equations (14) and (13).

Summary Statistics: $R^2 = 0.98$
Log of Likelihood Function = 6022

Table 5. Total Cost Function Estimated Coefficients and Summary
(cont'd) Statistics, Final Model, Canadian Food and Beverage Industries, 1961-1982

Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio
α_{412}	0.010	12.9	α_{516}	0.536	100.3	α_{h4}	0.014	0.0
α_{413}	0.010	12.8	α_{517}	0.695	113.2	α_{h5}	-0.015	-0.2
α_{414}	0.014	18.2	α_{q1}	1.081	12.3	α_{h7}	-0.010	-0.5
α_{415}	0.019	24.3	α_{q2}	0.988	10.8	α_{h9}	-0.061	-0.4
α_{416}	0.013	17.4	α_{q3}	0.905	8.4	α_{h10}	0.119	0.4
α_{417}	0.006	6.8	α_{q4}	0.816	5.1	α_{h13}	-0.694	-7.0
α_{51}	0.843	153.7	α_{q5}	1.061	2.4	α_{h14}	-0.155	-0.6
α_{52}	0.826	138.8	α_{q6}	0.932	5.3	α_{hhi}	0.134	2.2
α_{53}	0.747	142.5	α_{q7}	1.040	13.4	α_{t}	-0.001	-0.8
α_{54}	0.742	136.7	α_{q8}	1.080	11.8	β_{11}	0.039	4.9
α_{55}	0.808	146.1	α_{q9}	0.895	3.9	β_{12}	-0.008	-1.4
α_{56}	0.783	145.9	α_{q10}	0.725	5.0	β_{13}	0.022	4.2
α_{57}	0.843	146.4	α_{q11}	0.814	5.4	β_{14}	-0.005	2.6
α_{58}	0.628	119.4	α_{q12}	0.944	19.1	β_{15}	-0.057	-14.7
α_{59}	0.580	104.2	α_{q13}	0.748	8.9	β_{22}	-0.050	6.7
α_{510}	0.658	116.6	α_{q14}	1.319	8.9	β_{23}	0.013	2.6
α_{511}	0.762	135.2	α_{q15}	0.932	13.9	β_{24}	-0.003	-1.7
α_{512}	0.867	161.6	α_{q16}	0.822	11.1	β_{25}	-0.053	-14.1
α_{513}	0.759	137.4	α_{q17}	0.909	18.3	β_{33}	-0.006	-1.1
α_{514}	0.634	109.9	α_{h2}	0.170	2.2	β_{34}	-0.003	-1.7
α_{515}	0.623	109.5	α_{h3}	0.118	1.1	β_{35}	-0.026	-8.1

Table 5. (cont'd) Total Cost Function Estimated Coefficients and Summary Statistics, Final Model, Canadian Food and Beverage Industries, 1961-1982

Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio
β_{44}	0.012	18.4	β_{1h}	0.012	4.3	β_{4t}	0.0001	2.2
β_{45}	-0.012	-15.0	β_{2h}	0.007	2.9	β_{5t}	0.0014	4.8
β_{55}	0.148	19.3	β_{3h}	-0.010	-4.6	β_{qq}	0.361	3.1
β_{1q}	-0.010	-2.6	β_{4h}	-0.001	-1.8	β_{qh}	0.358	2.7
β_{2q}	-0.019	-5.6	β_{5h}	-0.008	-1.6	β_{hh}	-0.092	-0.7
β_{3q}	-0.011	-3.7	β_{1t}	-0.0002	-0.9			
β_{4q}	-0.003	-4.4	β_{2t}	-0.0009	-3.9			
β_{5q}	0.043	6.2	β_{3t}	-0.0005	-2.7			

Table 6. Production Labour Share Equation Estimated Coefficients and Summary Statistics, Final Model, Canadian Food and Beverage Industries, 1961-1982[1]

Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio
α_{21}	0.085	25.1	α_{210}	0.158	45.3	β_{22}	0.050	6.7
α_{22}	0.108	32.4	α_{211}	0.088	24.7	β_{23}	0.013	2.6
α_{23}	0.140	46.8	α_{212}	0.041	12.8	β_{24}	-0.003	-1.7
α_{24}	0.117	34.5	α_{213}	0.090	26.9	β_{25}	-0.053	-14.1
α_{25}	0.006	20.1	α_{214}	0.098	28.9	β_{2q}	-0.019	-5.6
α_{26}	0.083	24.1	α_{215}	0.105	30.5	β_{2h}	0.007	2.9
α_{27}	0.057	17.2	α_{216}	0.151	43.3	β_{2t}	-0.0009	-3.9
α_{28}	0.179	56.7	α_{217}	0.088	24.8			
α_{29}	0.182	56.9	β_{12}	-0.008	-1.4			

[1] The final model is the system of equations (14) and (13).

Summary Statistics: $R^2 = 0.95$
Log of Likelihood Function = 6022

Table 7. Non-Production Labour Share Equation Estimated Coefficients and Summary Statistics, Final Model, Canadian Food and Beverage Industries, 1961-1982[1]

Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio
α_{31}	0.036	13.0	α_{310}	0.084	30.2	β_{23}	0.013	2.6
α_{32}	0.028	10.0	α_{311}	0.041	14.6	β_{33}	-0.006	-1.1
α_{33}	0.043	17.0	α_{312}	0.024	8.3	β_{34}	-0.003	-1.7
α_{34}	0.062	22.8	α_{313}	0.075	27.4	β_{35}	-0.026	-8.1
α_{35}	0.070	25.6	α_{314}	0.153	53.8	β_{3q}	-0.011	-3.7
α_{36}	0.048	17.1	α_{315}	0.094	33.8	β_{3h}	0.010	-4.6
α_{37}	0.041	14.7	α_{316}	0.122	44.8	β_{3t}	-0.0005	-2.7
α_{38}	0.098	37.5	α_{317}	0.089	29.4			
α_{39}	0.136	49.2	β_{13}	0.022	4.2			

[1] The final model is the system of equations (14) and (13).

Summary Statistics: $R^2 = 0.96$
Log of Likelihood Function = 6022

Table 8. Energy Share Equation Estimated Coefficients and Summary Statistics, Final Model, Canadian Food and Beverage Industries, 1961-1982[1]

Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio
α_{41}	0.003	3.6	α_{410}	0.008	10.6	β_{24}	-0.003	-1.7
α_{42}	0.007	8.6	α_{411}	0.017	22.2	β_{34}	-0.003	-1.7
α_{43}	0.010	14.5	α_{412}	0.010	12.9	β_{44}	0.0[illegible]2	18.4
α_{44}	0.010	12.8	α_{413}	0.010	12.8	β_{45}	-0.012	-15.0
α_{45}	0.011	14.4	α_{414}	0.014	18.2	β_{4q}	-0.003	-4.4
α_{46}	0.006	8.0	α_{415}	0.019	24.3	β_{4h}	-0.001	-1.8
α_{47}	0.009	12.1	α_{416}	0.013	17.4	β_{4t}	0.0001	2.2
α_{48}	0.008	11.1	α_{417}	0.006	6.8			
α_{49}	0.020	26.5	β_{14}	0.005	2.6			

[1] The final model is the system of equations (14) and (13).

Summary Statistics: $R^2 = 0.89$
Log of Likelihood Function = 6022

Table 9. Materials Share Equation Estimated Coefficients and Summary Statistics, Final Model, Canadian Food and Beverage Industries, 1961-1982[1]

Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio	Coefficient	Estimated Value	Asymptotic t-ratio
α_{51}	0.843	153.7	α_{510}	0.658	116.6	β_{25}	-0.053	-14.1
α_{52}	0.826	138.8	α_{511}	0.762	135.2	β_{35}	-0.026	-8.1
α_{53}	0.747	142.5	α_{512}	0.867	161.6	β_{45}	-0.012	-15.0
α_{54}	0.742	136.7	α_{513}	0.759	137.9	β_{55}	0.148	19.3
α_{55}	0.080	146.1	α_{514}	0.634	109.9	β_{5q}	0.043	6.2
α_{56}	0.783	145.9	α_{515}	0.623	109.5	β_{5h}	-0.008	-1.6
α_{57}	0.843	146.4	α_{516}	0.536	100.3	β_{5t}	0.0014	4.8
α_{58}	0.628	119.4	α_{517}	0.695	113.2			
α_{59}	0.580	104.2	β_{15}	-0.057	-6.7			

[1] The final model is the system of equations (14) and (13).

Summary Statistics: $R^2 = 0.97$
Log of Likelihood Function = 6022

and kurtosis indicated a degree of non-normality and non-randomness, which appeared to be caused by some autocorrelation and outliers, with the residuals for miscellaneous food processors and soft drink manufacturers displaying the largest deviations from zero. We did not correct for these problems since they affect only the efficiency of our tests (i.e., the strength of inferences drawn from the results), and do not create biases in the magnitudes of the estimated coefficients. Nevertheless, correction for such problems, and possible exclusion of the miscellaneous processors (a very heterogeneous group of industries) would be a useful matter for future research.

4.5.2 Tests for Concavity

As opposed to the other regularity conditions on the cost function mentioned in Section 4.2, concavity in input prices w_{rt} is not built into the TL cost function, nor is it imposed, like linear homogeneity in prices, in estimation. Thus, it is necessary to test for negative semi-definiteness of the Hessian matrix (of second-order partial derivatives with respect to input prices) of the cost function. In particular, the characteristic roots, or eigenvalues of this matrix must all be non-positive, and at least one must be zero (Hadley 1961, p. 256). Since symmetry is imposed, all the eigenvalues will be real (ibid, p. 240); thus, the possibility of imaginary roots is ruled out. Unlike the other tests mentioned above, this test has no 'level of significance'; concavity is either satisfied or violated.

There are two ways of testing for concavity. The first is a global test which if satisfied, indicates that concavity holds for the whole sample. If the former test fails, concavity must be tested for at each observation.

Diewert and Wales (1985), provide a method for making both tests. The Hessian matrix H for the TL cost function is defined as:

$$H = B - \hat{S} + SS' , \tag{15}$$

where: B is the symmetric (5x5) matrix of estimated price coefficients from the cost/share system

S is the (1x5) share vector: $(S_1\ S_2\ S_3\ S_4\ S_5)'$

S' is the transpose of S, and

$\hat{S}$ is a (5x5) diagonal matrix which has the vector S on its diagonal (and zeroes elsewhere).

For a global test, they show that provided the share vector is non-negative, the matrix $-(S - SS')$ is negative semi-definite and therefore a necessary and sufficient condition for global concavity is that B be negative semi-definite (ibid., p. 9). The global test with the final model yielded 3 positive eigenvalues. This is not a surprising result, since concavity restrictions are typically rejected at some points - Diewert and Wales base their development and analysis of globally concave functional forms on this premise.

Since B isn't negative semi-definite then it must be evaluated at each sample point using the predicted shares from (13) (i.e., those generated from the model using observed input prices, output, concentration level, and time period for each industry) rather than the observed shares.[19] We evaluated the eigenvalues for H for each of the 374 observations. Of these, 258 or 69 percent had some positive eigenvalues. The number of positive eigenvalues per violation within each industry ranged from a minimum of 1 to a maximum of 3. In the former case, the positive values were often very small, but since it is not possible to determine the 'statistical significance' of these violations, we must assume that concavity is indeed violated where positive eigenvalues exist.

The number of concavity violations observed here wouldn't seem to imply that our estimates are biased, though. As Wales (1977) points out, a violation of regularity conditions (concavity) in practice does not preclude the obtaining of good price ... elasticity estimates" (p. 191). Moreover, results from Diewert and Wales (1985 - Tables 1 to 5) imply a relatively high degree of consistency between those estimates obtained from their globally concave forms and the unconstrained TL estimates. Even though their unconstrained TL violated concavity for 24 percent of observations as opposed to 69 percent here, it can only be assumed that the higher number of violations for this sample does imply inaccurate parameter measurement.

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[19] Predicted shares are used in order to remove the stochastic element from evaluation of these terms. Actual shares should not be used since we can only explain that proportion of their change accounted for by the model; inclusion of the remaining stochastic element would tend to yield false results.

4.6 Results from the Final Model

4.6.1 Estimated Elasticities of Factor Demands

The input demand elasticities which can be derived from dual cost functions are an important source of information and are usually the focal point in assessing both the reliability of a dual model and the sample used in estimation.[20] If the elasticities are typically far from levels predicted by economic theory and knowledge of the sample, the model or data must be reassessed. Thus, although the objective of this study is to investigate concentration effects on costs, the input demand elasticities generated should provide a reasonable guide to the validity and stability of the model.

Own price input demand elasticities are calculated using the expression

$$(16) \qquad \varepsilon_i = \frac{(\beta_{ii} + (S_i^2) - S_i)}{S_i}, \; i = 1,2,..,5 \; .$$

See Berndt and Wood (1975) for a derivation of this relationship. Factor index 'i' refers to capital for i=1, production labour (i=2), non-production labour (i=3), energy (i=4) and materials (i=5). This expression is evaluated at the average predicted shares for each industry. Predicted shares are obtained using the 1961-1982 average input prices, output, concentration level and time period with the estimated coefficients of Table 5 for each industry[21]. Cross-price elasticities are similarly estimated using the expression:

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[20] A second useful source of information is the Allen-Uzawa elasticities of substitution which relate cross-substitution or complementarily between factors of production. Results from these calculations can be found in Cahill (1986, p. 122).

$$(17) \qquad \epsilon_{ij} = \frac{(\beta_{ij} + S_i S_j)}{S_i}, \ \forall \ i \neq j \ ; \ i,j = 1,2,..,5 \ .$$

Results from these calculations are given in Table 10.

The own elasticities for capital, production labour and non-production labour are generally of the right sign, with the exception of ϵ_k for Slaughtering and Meat Processors, Poultry Processors, Dairy Products and Feed Mills and ϵ_{lp} for Dairy Products, Feed Mills and Vegetable Oil Mills. Of these positive elasticities, three are close enough to zero to be acceptable; their positive signs are probably due to measurement error. Similarly, for ϵ_m, the positive elasticities observed are are small enough to be assumed insignificantly different from zero. The most unstable own price elasticities are for energy; 7 of the 17 industries had positive values for ϵ_e.[22].

Although initially puzzling, the unstable energy elasticity estimates seem to result from the extremely small cost share of this input (on average about 1.5 percent of total cost for all industries -see Table 4).[23] Thus, energy share equation

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[21] Predicted shares are used for the same reason given for concavity tests.

[22] We did not construct confidence intervals for these statistics, but methods do exist to establish these. See, for example, Anderson and Thursby (1986), or Moroney and Trapani (1981 fn. 5, p. 69).

[23] Anderson and Thursby (1986) observe that "elasticity estimators based on smaller cost shares generally display wider confidence intervals, ceteris paribus" (p. 655). Thus, the positive energy estimates here could just as well have been negative, given the likely variances involved.

Table 10. Estimated Own and Selected Cross Price Elasticities of Factor Demands, Canadian Food and Beverage Industries, 1961-1982

Industry Name	own-price elasticities[1]					selected cross-price elasticities		
	ϵ_k	ϵ_{lp}	ϵ_{lnp}	ϵ_e	ϵ_m	ϵ_{lpk}	ϵ_{lnpk}	ϵ_{ek}
slaughtering and meat processors	0.60	-0.18	-1.20	1.10	0.04	-0.10	0.81	0.82
poultry processors	1.09	-0.35	-1.26	0.37	0.03	-0.07	0.53	-0.05
fish processors	-0.20	-0.48	-1.14	-0.04	-0.04	-0.01	0.66	0.41
fruit & vegetable processors	-0.34	-0.40	-1.06	-0.06	-0.04	-0.01	0.47	0.41
dairy products	0.04	0.06	-1.04	-0.11	0.01	-0.12	0.39	0.37
flour and breakfast cereals	-0.38	-0.13	-1.13	0.50	0.00	-0.06	0.64	0.63
feed mills	0.04	0.33	-1.16	0.11	0.05	-0.17	0.71	0.45
biscuits	-0.43	-0.53	-0.98	0.16	-0.12	0.03	0.32	0.51
bakeries	-0.40	-0.53	-0.92	-0.44	-0.15	0.02	0.24	0.28
confectionery	-0.45	-0.50	-1.01	0.20	-0.09	0.02	0.38	0.53
cane and beet sugar processors	-0.44	-0.17	-1.18	-0.37	-0.01	-0.04	0.81	0.31
vegetable oil mills	-0.11	1.21	-1.44	-0.01	0.07	-0.31	1.58	0.41
miscellaneous processors n.e.s.	-0.27	-0.22	-1.02	-0.02	-0.02	-0.56	0.38	0.42
soft drinks	-0.50	-0.32	-0.90	-0.28	-0.12	0.00	0.24	0.36
distilleries	-0.60	-0.36	-0.98	-0.44	-0.13	0.07	0.40	0.36
breweries	-0.60	-0.49	-0.94	-0.26	-0.18	0.11	0.36	0.45
wineries	-0.57	-0.31	-0.99	0.21	-0.09	0.03	0.38	0.58
for whole sample[2]	-0.41	-0.36	-1.03	-0.09	-0.05	-0.01	0.41	0.42

[1] All elasticities are estimated at industry sample means - see expressions (16) and (17) for derivation of these.

[2] Evaluated at all-industry mean shares.

estimates are likely to be unstable in a statistical sense, since this input is usually overwhelmed by the others. Problems with energy elasticities have been encountered in other studies as well, notably Fuss (1975) and Hall (1986). In both cases, static models similar to that employed here were estimated. For the Canadian food and beverage industry, Fuss set all the energy elasticities to zero. In Hall's international comparison of energy consumption, he found that for gas, the elasticities generated for some periods were positive.

The positive elasticities observed for capital and production labour cannot be explained on the basis of small cost shares, and so are less easily justified.[24] Part of the problem may be due to the fact that these inputs are less readily changed in response to changes in their prices. Capital adjustment costs and wage ridgidities - features not allowed for in our model - might account for this. In relation to the rest of the (negative or close to zero) elasticities observed for these variables, it would seem that these violations are minor, however, and not sufficient to suggest that the model employed here is inappropriate.

Aside from these considerations, it is still useful to summarize the general results from these estimates. Overall, we find that capital demand has been quite price inelastic, as has been demand for production labour; both sets are relatively stable between industries (other than the exceptions listed) and range between -0.10 and -0.60. Interestingly, non-production labour demand has been relatively elastic in most cases. This is possibly due to a lower level of unionization for this group. At the very least, it indicates that aggregation of production and non-production labour is likely to be rejected, and that interesting information would have been lost if such aggregation had been imposed a priori. Not surprisingly, all materials elasticities are very low, reflecting the limited possibilities of substitution between materials and other inputs in food processing.

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[24] As with our energy elasticities, our problems with capital and labour are not unique. For a somewhat different time period and at the 2-digit level of industry aggregation (food and beverages) Cameron and Schwartz (1979) p. 114, observed positive own elasticities for their capital and (aggregate) labour variables.

The cross-elasticities given indicate a dominant complementarity between production labour and capital - the exceptions to this are close to zero. This result is quite different from that for capital and non-production labour where strong substitutability is evident, possibly due to an increased trend towards mechanization in management.

4.6.2 Estimated Concentration Effects on Average Costs and Choice of Inputs

We shall measure the impacts of concentration changes on the industries being studied in two ways. First, we establish the extent to which concentration changes resulted in changes in average costs of production in each industry. This effect is measured, in terms of the basic model (11) as:

$$\epsilon_{ch} = \frac{\partial AC}{\partial h} \cdot \frac{h}{AC} = \left(\frac{\partial C(w,Q,h,t)}{\partial h}\right) \cdot \frac{h}{AC} , \tag{18}$$

(the subscripts r and t are dropped from this expression for simplification - this procedure will be adopted for all future notation). Thus, we can use the total cost function C(w,Q,h,t) to measure the effects of changes in h on average costs so long as we assume that $\partial Q/\partial h$ is zero. The reasoning here is that changes in concentration should not have any effect on the magnitude of industry output; rather, we would expect only the way in which firms share the production of industry output to change (i.e., changes in market shares).

Equation (18) is carried over to the estimated model (14) as follows:

$$(19) \qquad \epsilon_{chr} = \frac{\partial ln C(w,Q,h,t)}{\partial ln h} = \alpha_{hr} + \alpha_{hhi} + \sum_{i=1}^{5} \beta_{ih} ln w_i + \beta_{qh} ln Q + \beta_{hh} ln h \; ; \; \forall \; r.$$

As with the input demand elasticities, (19) is evaluated at the sample means for each industry. Results are given in Table 11. Even though β_{hh} was insignificant by its t-ratio, as were the α_{hr}'s for most of the low-concentration industries (see Table 5), both terms were included in the calculations since it was felt that these variables were still relevant.

Of central interest is whether a pattern exists between ϵ_{ch} and the average concentration level of each industry. By assessing the results in this way, we can incorporate the influences of differences in levels of concentration between industries and relate these to the time-series effects of changes in concentration. Thereby we can account for possible differences in effects of changes in concentration on costs between low- and high-concentration industries, as postulated by both Peltzman

Table 11. Estimated Returns to Concentration, Canadian Food and Beverage Industries, 1961-1982 (Ranked by Average Concentration Level)

industry name	S.I.C.	average concentration level	concentration level (1982)[1]	average value of (ϵ_{ch})[2]
feed mills	106	2.8	2.4	-0.12
bakeries	1072	3.5	3.6	-0.08
dairy products	104	3.6	5.4	-0.01
poultry processors	1012	4.5	5.1	0.19
fruit & vegetable processors	103	4.5	4.4	0.00
miscellaneous processors n.e.s.	1089	5.0	4.6	-0.68
fish processors	102	6.2	6.4	0.13
soft drinks	1091	8.2	10.3	-0.19
confectionery	1081	8.9	8.6	0.10
slaughtering and meat processors	1011	10.4	6.6	0.13
flour and breakfast cereals	105	13.6	11.8	0.15
wineries	1094	15.7	15.4	0.06
biscuits	1071	17.1	19.7	0.15
vegetable oil mills	1083	20.3	15.4	0.15
cane and beet sugar processors	1082	22.2	21.4	0.13
distilleries	1092	25.0	21.6	0.11
breweries	1093	30.7	30.7	0.13

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[1] This series is given to indicate how the most recent concentration data - which are probably more indicative of today's concentration levels - relate to ϵ_{ch}. While the rankings are more-or-less the same (only one case each of a switch from low to high and high to low), it can be seen that concentration increased in only one high-concentration industry relative to average, although this belies an actual increase in concentration in the breweries industry since 1971. Low-concentration industries have had a much different pattern, however, since here the majority (five) had a higher concentration level in 1982 relative to average, reflecting more concentration growth in this group.

[2] All returns to concentration (see (19)) estimates made at industry sample means.

(1977) and Gisser (1982, 1984). As an inspection of Table 11 shows, ϵ_{ch} is positive for all high-concentration industries. In contrast, 5/9 low-concentration industries have a negative ϵ_{ch}, with 3/9 positive and one with no relationship between concentration and cost. Thus, it would appear that for the industries considered, increases in concentration in high-concentration industries consistently raised industry average costs, while increases in low-concentration industries generally caused average costs to fall. This pattern is consistent with the result obtained by Gisser (1984) for his sample, and suggests that cost effects of concentration increases are quite different, on average, in low versus high-concentration industries.

A reasonable conclusion about the relationship between average concentration levels and the sign of ϵ_{ch}, is that increases of concentration in low-concentration industries have generally meant lower costs of production industries up to an average concentration level of around 8.9. Increases in concentration for industries with average concentration levels higher than this seem to have increased average costs, although not too much emphasis should be placed on this level of concentration. Rather, it would seem more sensible to specify a range (say, up to an average concentration level of h=10), beyond which we can be relatively certain that increases in concentration led to increases average costs.[25,26]

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[25] We checked in further depth the relationship between average concentration levels and ϵ_{ch} by regressing ϵ_{ch} on average h. The adjusted R^2 for this regression was 0.13; The

From the results outlined in Table 11, in spite of the fact that average concentration levels were small on average, mergers of companies with large market shares in the poultry processor and fish products industries ought to have been investigated at least, to determine effects of such mergers on costs. And we would guess that even today, on the basis of data in Table 11, proposed mergers of high market share companies in any of the following industries:

- slaughtering and meat processors
- flour and breakfast cereals
- biscuit manufacturers
- confectionery
- cane and beet sugar processors
- vegetable oil mills

25(cont'd) coefficient on h was .011 and its t-ratio was 1.83 (significant at 90% level of confidence). The intercept estimate was -.11, with a t-ratio of -1.26 (significant at about 80% confidence). Refinements - elimination of miscellaneous industries (an outlier) and setting the intercept to zero - raised the R^2, lowered size of the coefficient on h by half and raised the t-ratio on it, but did not affect the qualitative conclusion: ϵ_{ch} gets larger (and more positive) as concentration rises for this sample.

[26] Another reason for choosing h=10 is that this has been identified as a level below which all mergers are permitted in the U.S. under recent U.S. Merger Guidelines; proposed mergers in markets with $10 < h < 18$ will be scrutinized on a number of grounds (among them efficiency), while proposed mergers in markets with $h > 18$, will generally be blocked (Salop 1987, p. 8). Both Schmalansee (1987), p. 40) and White (1987, p. 17) find little wrong with the limits. It is interesting that the U.S. Merger Guidelines seems to be far more explicit about structure and allowable mergers than the new Canadian Competition Act, suggesting more ambiguity and latitude in the latter with respect to concentration levels and potential increases in these.

- distilleries
- breweries
- wineries

should be reviewed with both potential market power and potential efficiency losses kept in mind. As we will see, employment effects might be a factor, if the merging firms can show that employment (not unemployment) will increase.

Aside from establishing the overall effect of concentration on average costs, a matter of additional interest is the effect which increasing concentration has had on the relative use of various factors of production. An indicator of the impact of concentration on factor demands is the sign of β_{ih} for each of the five inputs in the cost function. An inspection of Table 5 indicates that increases in concentration led to increased cost shares for capital and production labour, while cost shares for non-production labour, energy and materials decreased. These coefficients are, however, not fully informative, since in referring to shares they include both the effects of concentration on total costs and factor demands (concentration is assumed to have no effect on factor prices for econometric reasons, and so countervailing power effects and oligopsony in factor markets are ruled out). To obtain a more accurate notion of concentration 'bias', we must separate these effects, and merely 'distill' the factor demand bias. In terms of the most general model, the concentration bias effect is:

$$(20) \qquad \epsilon_{ih} = \left[\frac{\partial X_i(w,Q,h,t)}{\partial h}\right] \cdot \frac{h}{X_i} \qquad \forall\ i.$$

Thus, if (20) is positive, increases in concentration increase the use of factor i, and if this term is negative, increases in concentration decrease its use. With regard to our final model, (20) is measured as:

$$(21) \qquad \epsilon_{ihr} = \frac{(\beta_{ih} + \epsilon_{chr} \cdot S_i)}{S_i} \quad ; \quad \forall\ i,r.$$

The estimated values for ϵ_{ihr}, evaluated at the industry sample means are presented in Table 12.

For most industries, there was a tendency for increases in concentration to cause increases in the use of both capital and production labour, while use of non-production labour generally decreased as concentration rose. The results for energy and materials demands are less consistent, with 8/17 industries with a negative concentration-energy bias elasticity and 6/17 with a negative concentration-materials bias elasticity. Whereas the (absolute) magnitude of ϵ_{chr} is rather low for most industries, factor demands are more elastic to changes in concentration. For capital, a 1 percent increase in concentration led, in general to between a .20 and .50 percent increase in demand for that factor. The concentration-production labour elasticities are of roughly the same (absolute) magnitude, while the effects on non-production labour, energy and materials are somewhat smaller.

One criterion often used in judging the desirability of structural change in the manufacturing sector is the effect which such change has on employment. Already, we have seen that for all of the industries studied there has been a substitution

Table 12. Estimated Bias of Concentration by Input, Canadian Food and Beverage Industries, 1961-1982

	biases by factor (input)[1]				
Industry Name	ϵ_{kh}	ϵ_{lph}	ϵ_{lnph}	ϵ_{eh}	ϵ_{mh}
slaughtering and meat processors	0.61	0.24	-0.22	-0.03	0.12
poultry processors	0.81	0.27	-0.26	0.08	0.18
fish processors	0.35	0.19	-0.15	0.05	0.12
fruit & vegetable processors	0.18	0.08	-0.18	-0.07	-0.01
dairy products	0.29	0.14	-0.17	-0.08	-0.02
flour and breakfast cereals	0.32	0.27	-0.11	0.03	0.14
feed mills	0.18	0.07	-0.42	-0.20	-0.13
biscuits	0.30	0.20	0.04	0.06	0.14
bakeries	-0.08	-0.03	-0.15	-0.12	-0.09
confectionery	0.24	0.15	-0.04	0.00	0.09
cane and beet sugar processors	0.27	0.24	-0.21	0.08	0.12
vegetable oil mills	0.40	0.47	-0.55	0.07	0.14
miscellaneous processors n.e.s.	-0.48	-0.58	-0.83	-0.76	-0.69
soft drinks	-0.07	-0.11	-0.26	-0.25	-0.21
distilleries	0.19	0.19	0.00	0.07	0.10
breweries	0.20	0.18	0.04	0.07	0.11
wineries	0.15	0.14	-0.06	-0.04	0.04

[1] All elasticities are estimated at industry sample means. See (21) for derivation of this term.

effect between capital and non-production labour, while for production labour this effect has often been reversed. Of additional interest here, then, is the effect concentration increases or decreases have had on overall employment (i.e., number of employees). At first glance, the results of Table 12 seem to indicate a general increase in the employment of production workers (measured in hours), while non-production worker numbers have decreased as concentration increased.

To pursue this result further, average effects on total employment are calculated, using a 2000-hour year for each production worker and evaluating the elasticities at the average production and non-production worker employment levels for each industry. Thus, a total employment effect is calculated (for each industry) as:

$$(22) \qquad \Delta E_r = \epsilon_{lphr} \cdot (Q_{lpr}/2000) + \epsilon_{lnphr} \cdot Q_{lnpr} \quad \forall\ r ,$$

where: ΔE_r is the total employment effect of a 1 percent increase in the average concentration level in industry r, and all other variables are as defined previously.

The results of these calculations are presented in Table 13, with overall employment results given in the last column. Of the 17 industries, the majority (12) show increases in employment due to increases in concentration, ceteris paribus; the converse is also true. The five overall decreases observed were experienced in low-concentration industries, indicating that there may be a conflict between the social benefits due to increasing concentration in these industries: lower average

Table 13. Simulated Average Employment Effects of Increases in Concentration, Canadian Food and Beverage Industries, 1961-1982

	average number employed		average change in employment from 1% change in h		
Industry Name	Prod'n (Q_{lp})	Non-Prod'n (Q_{lnp})	ΔQ_{lp}	ΔQ_{lnp}	Net Change ΔE[1]
slaughtering and meat processors	22591	8249	54	-18	+36
poultry processors	6499	1087	18	-3	+15
fish processors	16888	3016	32	-5	+27
fruit & vegetable processors	13797	4446	11	-8	+3
dairy products	14311	15500	20	-26	-6
flour and breakfast cereals	3330	1871	9	-2	+7
feed mills	5447	3695	4	-16	-12
biscuits	4857	1868	10	1	+11
bakeries	17494	11419	-5	-17	-22
confectionery	7154	2585	11	-1	+10
cane and beet sugar processors	2137	738	5	-2	+3
vegetable oil mills	591	276	3	-2	+1
miscellaneous processors n.e.s.	10566	7281	-61	-60	-121
soft drinks	5851	8056	-6	-20	-26
distilleries	2932	2460	6	0	+6
breweries	5732	4444	5	2	+7
wineries	549	441	1	0	+1

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[1] See expression (22).

costs have been attained at the expense of overall employment. Obviously, social benefit criterion being used will govern the way in which we judge how beneficial increases in concentration have been in the low-concentration sectors. Two caveats apply to the above analysis, though.

First, it should be recalled that out-of-sample use of the elasticities obtained may lead to faulty inferences, even if the model accurately reflects behaviour over the period studied. The above calculations come close to violating this rule, since they are evaluated in terms of artificial and not actual changes. Thus, they are probably best accepted as a very rough guide to what might have occurred had increases in concentration happened, and only serve to illustrate the possible trade-offs between cost minimization and employment.

Second, note that the result indicated for miscellaneous industries should be viewed with scepticism. Given the heterogeneity of this industry, and the inability of the model to accurately explain its behaviour, not too much faith should be placed in this very large employment change, since it is probably subject to a larger error than the other figures.

4.6.3 Explaining Concentration Effects on Costs

4.6.3.1 Introduction

Questions still remain as to why high-concentration industries appear to be affected differently from low-concentration industries in terms of average costs when concentration increases or decreases. We might speculate about many possible causes for this behaviour, but we restrict ourselves to evidence which can be gleaned from the modelling framework employed. In particular, three possibilities are considered : differential rates of technical change, differences in the extent of returns to scale (i.e., whether industries produce on the downward, upward or bottom portion of their average cost curves); and the extent to which output differed from the minimum-average-cost output level over the period studied.

4.6.3.2 Technical Change

Technical change is measured in three ways here. Hicks-neutral technical change is measured by the parameter α_t in (14). This measures the extent to which technical change of the sort that reduces all factors of production equally, or homothetically, has occurred. As can be seen, the t-ratio, at -0.8, indicates that the null hypothesis that no neutral technical change occurred in any industry cannot be rejected[27]. In other words, this result suggests that there has been no significant technical change of this type.

As second measure of technical change is the 'dual rate of total cost diminution'. The terminology and method are drawn from Berndt and Khaled (1979, p.122). An equivalent derivation from (12) is:

$$(23) \qquad \epsilon_{ctr} = \frac{\partial lnC(w,Q,h,t)}{\partial t} = \alpha_{tr} + \sum_{i=1}^{5} \beta_{it} lnw_i + \beta_{qt} lnQ + \beta_{ht} lnh + \beta_{tt} \cdot t$$

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[27] Recall that in Section 4.4.2, hypothesis test results showed that differences in α_{tr} across industries were weak or non-existent and so equality of this term for all industries was imposed when estimating the system (14) and (13).

Expression (23) combines the neutral and input bias components for each industry, thus measuring the decrease in average costs each year (on average) due to overall technical change.[28] It is closely linked to the notion of total factor productivity discussed in Chapter 3. We evaluated (23) using the sample averages for each industry with results ranging from between -.0010 to -.0013, showing an almost insignificant amount of reduction in costs attributable to overall technical change (i.e., between .1% and .13% per year). Obviously, with numbers this small, it would be difficult to detect a pattern with regards to concentration levels, and since the results were so similar for all industries, they are not shown here. Moreover, when α_t was set to zero, ϵ_{ctr} became positive, now positive, now ranging between 0.0001 and 0.004, but still probably insignificantly different from zero. This result confirms that of Denny Fuss and Waverman (1979, p. 90), who found that for their Canadian food and beverage sample, only a very minor amount of technical change occurred ($\epsilon_{ct} = 0.002$), indicating an increase in costs of 0.2% per year the period 1962-1975 (as opposed to a significant decrease in costs of between 1 and 2.4% per year for most other industries included in their study). Their result for food and beverages was insignificantly different from zero, however, as was their coefficient for neutral technical change.

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[28] Along with the restriction that $\alpha_{tr} = \alpha_t$, (14) was estimated with $\beta_{qt} = \beta_{ht} = \beta_t$ (see Section 4.4.2). Thus, our restricted measurementof (23) has only the first two terms, with α_t substituted for α_{tr}.

Denny, Fuss and Waverman's results are also consistent with our results from Chapter 3 where the average yearly productivity change ranged from an improvement of 1.3 percent in feed industry: 12%/9 years) to a deterioration of 1.1% in the biscuits industry, but with overall productivity growth of close to zero (0.12% per year) for all food and beverage industries combined. That our estimates here differ somewhat in magnitude from those of Chapter 3 is unimportant - both model and data differences inevitably imply that measurements will not be the same. The point is that both of our techniques suggest that annual productivity changes for individual (4-digit S.I.C.) food and beverage industries lay between about +1.3% and -1.1% with average amount of change for the sector as a whole close to 0.1% per year improvement, as opposed to .67% per year for all-of-manufacturing.

Johannsen (1981) obtained quite similar results. He estimated that only modest changes in TFP for most (3-digit) industries occurred over the period 1962 to 1977, with some decreases, and an overall growth rate of only 0.35 % per year for the sector. He also found that most of the growth that did occur was due to change in the first half of the period studied (1962-1969) - in all but one industry productivity worsened in the latter portion of the sample's time period (1970-1977).

In a more recent study, Lopez (1984) noted that for the sector as a whole "productivity growth has been steady throughout the period [1961-1979] and ... has led to an almost 0.5 percent average annual decline of the unit cost of production ... " (p. 229), suggesting a rate considerably higher than measurements from both methods used here and higher than Johannsen's estimate as well.

Salem (1987) found qualitatively similar effects to those measured by Johannsen; differences in productivity growth were observed for individual (4-digit) industries within the sector over the period 1962-1982, but with higher growth rates in the former half of the time period studied. Average productivity growth rates (over 1962-1982) within the sector ranged from an improvement of 1.12% per year (in the breweries industry) to a deterioration of -0.27% per year (for fish products). Overall, he found that sector productivity grew by 0.36% per year.

Although there is thus some difference between the various studies in the actual measurements of productivity obtained for the food and beverage sector for the two decades previous to 1982, there is no doubt that productivity growth was at best 0.5% per year and at worst was zero. Considering the apparent inconsistency of Lopez's estimate (0.5%) in comparison with results obtained both by us and other researchers, it is more likely that this growth rate was between zero and 0.35% per year over the period 1962-1982 and certainly closer to a range of zero to 0.1% per year for the 1970's. Whichever figure is used within each range, there is little doubt that productivity change in the food and beverage sector was considerably below that of most manufacturing sectors, as both all-of-manufacturing estimates cited above indicate. Thus, it would appear that while some industries within the sector have experienced productivity change close to or better than that of all-of-manufacturing, the overall food and beverage sector has made fewer cost-saving investments than non-food industries.

The very small amount of cost-reducing technical change generally observed for the food and beverage industries (relative to non-food industries) could probably be explained if it were considered to be a puzzle worth solving. For example, Carter (1985) found that, although the food, beverage and tobacco 'industry' accounted for 15 percent of total Canadian manufacturing sales in 1982, it only spent about 3 percent of the total R&D outlay for manufacturing. An extension of his figures back to 1976 shows that the share of total manufacturing R&D expenditures accounted for by this 'industry' has been consistently falling, from a high of 4.4 percent in that year. And if the tobacco industry were excluded from these data, the share of R&D for food and beverage industries alone would probably be even lower than this.

The final measure of technical change considered here is that of factor-specific technical change or technical bias. This is estimated by the parameter β_{it} for each input[29]. As can can be seen from Tables 5 to 9 (the capital bias term is b*%1t$** in Table 5), there was an insignificant capital-saving bias, significant labour-saving bias (for both types of labour) and significant energy and materials-using biases over the 1961-1982 period.

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[29] See Binswanger (1974) or Cahill (1986, pp. 39-41) for a more detailed discussion of technical bias. Like Binswanger, we assume constant rates of biases over time for each factor, but discuss only the direction of bias here, not the relative magnitude, given that bias is, by construction, the same for each industry.

These results are quite consistent with those of Denny, Fuss and Waverman (1979) - DFW - and Lopez (1984). Both studies obtained capital-using bias (in the DFW case this was insignificantly different from zero - the result here) and labour-saving bias, which is observed in the sample for both types of labour. Although they both found an energy-saving bias, DFW observed materials-using bias, as in this study, and Lopez found no evidence of bias towards or from materials use.

Overall, either due to results or imposed assumptions (i.e., that biases are equal for all industries) there is little evidence to suggest that there is a link between concentration levels and what little technical change occurred.

4.6.3.3 Returns to Scale

Returns to scale are estimated from (14) using the expression:

$$(24) \qquad \left(\frac{\partial AC}{\partial Q}\right) \cdot \frac{Q}{AC} = \{ (\alpha_{qr} + \sum_{i=1}^{5} \beta_{iq} \mathit{ln} w_i + \beta_{qq} \mathit{ln} Q + \beta_{qh} \mathit{ln} h) - 1 \} \quad \forall r ,$$

which is evaluated at the sample means for each industry[30]. This gives the average effect of a 1 percent change in output on average costs for each industry over the period 1961-1982. The results are presented in Table 14, which shows that 6/8 high-concentration industries and 7/9 low-concentration industries had increasing (indicated by a negative number) or

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[30] See Cahill (1986, p. 32) for a derivation of this term. It is adapted from Berndt and Khaled (1979, p. 1225).

Table 14. Estimated Dual Returns to Scale, Canadian Food and Beverage Industries, 1961-1982

Industry Name	Estimated Dual Returns to Scale[1]	Average h-index[2] level	Classification[3]
slaughtering and meat processors	0.064	10.4	h
poultry processors	-0.139	4.5	l
fish processors	-0.083	6.2	l
fruit & vegetable processors	-0.188	4.5	l
dairy products	0.008	3.6	l
flour and breakfast cereals	-0.034	13.6	h
feed mills	-0.005	2.8	l
biscuits	0.094	17.1	h
bakeries	-0.128	3.5	l
confectionery	-0.282	8.9	l
cane and beet sugar processors	-0.196	22.2	h
vegetable oil mills	-0.002	20.3	h
miscellaneous processors n.e.s.	-0.289	5.3	l
soft drinks	0.271	8.2	l
distilleries	-0.133	25.0	h
breweries	-0.152	30.7	h
wineries	-0.172	15.7	h

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[1] Evaluated at industry sample means - see (24) for a derivation of this term

[2] These data give the average concentration level (average value of Herfindahl index) for each industry.

[3] 'h' refers to those industries defined as 'high-concentration' (i.e. with h ≥ 10) - 'l' denotes low-concentration industries (i.e. with h < 10).

approximately constant returns to scale, while 2/8 and 1/9 respectively had decreasing returns to scale. Overall, these results suggest that there has been little difference between low- and high-concentration industries in terms the direction of scale effects. As we will see below, however, there does seem to have been systematic differences in the magnitude and persistence of unexploited scale effects between low- and high-concentration industries.

4.6.3.4 Optimal Output

Optimal output is calculated by differentiating average costs with respect to output, setting this term to zero and solving for Q. From (14), this is:

$$Q_r^* = \exp\{(1 - \alpha_{qr} - \sum_{i=1}^{5} \beta_{iq} \ln w_i - \beta_{qh} \ln h)/\beta_{qq}\} \quad \forall r \,, \tag{25}$$

which was estimated for each year studied and for the 17 food and beverage industries[31]. To relate average deviations of Q_r from Q_r^*,these are converted into percentage terms, or:

$$R_{qr} = \left[\frac{(Q_r - Q_r^*)}{Q_r^*}\right] \cdot 100 \quad \forall\ r. \tag{26}$$

If industry r is operating at the minimum point of its average cost curve, R_{qr} will equal zero, otherwise it will be greater than or less than this. Results from these calculations are presented in Table 15.

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[31] The second-order conditions for Q* to be a global minimum is that β_{qq} be > 0 - this is the case for our sample as Table 5 shows.

Although only the average values of R_{qr} are reported, Q* was calculated for every data point and so we can supplement these average results with a summary of the most frequent position of Q relative to Q*. Both indicators provide a useful means of determining how 'competitive' the industries were (and, probably, are)[32]. If we were to view any divergence from Q* as non-competitive behaviour, we would classify all 17 industries as non-competitive. Obviously, this is too demanding a rule, since there are many reasons why Q might diverge from its optimal level; errors in measurements made here are an obvious possible source of difference between Q and Q*. But those industries which consistently violate the perfectly competitive outcome obviously have structure in place (for example, entry barriers) which prevent a movement towards Q* over time.

There are nine cases where Q was consistently less or greater than Q*, we shall classify these industries as non-competitive (NC), with the rest competitive (C). Table 16 provides a comparison of the classifications obtained here and those posited in Chapter 2. As can be seen, conflicts exist for the Slaughtering and Meat, Fish Products, Flour and Breakfast Cereals, Biscuits, Bakeries and Cane and Beet Sugar Industries, or 5 out of the 15 available for comparison. Of these we would tend to side with the results of Chapter 2 and

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[32] It is well-known that perfectly competitive industries produce at Q* in long-run equilibrium, and in many regards it is considered socially optimal to produce here (in an efficiency sense). Thus, any divergence from this point suggests inefficiency.

Table 15. Estimated Optimal and Actual Output, Canadian Food and Beverage Industries, 1961-1982

Industry Name	Estimated Average Optimal Output[1] (Q*)	Average Actual Output[2] (Q)	Modal Condition[3]	Average % Deviation from Q* (R_{qr})[4]
slaughtering and meat processors	0.85	1.02	Q>Q* (22/22)	19.4
poultry processors	1.56	1.01	Q<Q* (13/22)	-18.6
fish processors	1.33	1.06	Q<Q* (15/22)	-15.3
fruit & vegetable processors	1.65	0.99	Q<Q* (22/22)	-40.3
dairy products	1.11	0.99	Q>Q* (13/22)	20.4
flour and breakfast cereals	1.17	1.06	Q<Q* (18/22)	-8.2
feed mills	0.95	0.97	Q>Q* (14/22)	1.7
biscuits	0.81	1.07	Q>Q* (16/22)	33.5
bakeries	1.37	0.95	Q<Q* (22/22)	-29.3
confectionery	2.08	0.96	Q<Q* (22/22)	-54.0
cane and beet sugar processors	1.68	0.98	Q<Q* (22/22)	-41.7
vegetable oil mills	1.08	1.17	Q<Q* (14/22)	4.1
miscellaneous processors n.e.s.	2.27	1.04	Q<Q* (22/22)	-51.7
soft drinks	0.43	0.93	Q>Q* (22/22)	132.9
distilleries	1.33	0.97	Q<Q* (22/22)	-29.0
breweries	1.11	1.04	Q<Q* (21/22)	-20.7
wineries	2.46	0.89	Q<Q* (15/22)	11.4

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[1] The average value for each industry was calculated using industry means values for the arguments of (25). Also note that since the second order conditions are fulfilled ($\beta_{qq} = 0.361 > 0$), Q* is the global minimum point on the average cost curve of each industry.

[2] This variable is scaled such that 1971=1.

[3] The ratio in parentheses gives the proportion of observations for which the modal condition holds. Thus, Q<Q* (T/22) means that Q was < Q* for T of the 22 years studied.

[4] See (26) for a derivation of this term.

Table 16. Comparison of Industry Classifications, Canadian Food and Beverage Industries

S.I.C.	Industry Name	Classification on Basis of Structure[1]	Classification on Basis of Optimal Output[2]
1011	Slaughtering and Meat Processors	C	NC
1012	Poultry Processors	C	C
102	Fish Products Industry	NC	C
103	Fruit and Vegetable Processors	NC	NC
104	Dairy Products	C	C
105	Flour and Breakfast Cereals	NC	C
106	Feed Mills	C	C
1071	Biscuits Manufacturers	NC	C
1072	Bakeries	C	NC
1081	Confectionery Manufacturers	NC	NC
1082	Cane and Beet Sugar Processors	C	NC
1083	Vegetable Oil Mills	C	C
1089	Miscellaneous Food Processors	-[3]	NC
1091	Soft Drink Manufacturers	NC	NC
1092	Distilleries	NC	NC
1093	Breweries	NC	NC
1094	Wineries	-	NC

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[1] Taken from classifications used in Chapter 2. Note that although these are divided into five groups, we shall limit our scope here to competitive (C) versus non-competitiven (NC), non-competitive industries are those with heterogeneous users, market power with heterogeneity or market power.

[2] NC industries are those with Q < or > Q* for all 22 observations - breweries with Q < Q* for 21 observations is treated as NC.

[3] '-' means comparison not possible. Recall that we dropped SIC's 1089 and 1094 from the analysis in Chapter 2.

classify Flour and Breakfast Cereals and Biscuits industries as non-competitive, since both have a high number of cases where output was less than or greater than Q*, respectively. This leaves the remaining three industries with contentious classifications. On the surface, there is no obvious reason why the conclusions might be different for these industries, but the inconsistencies noted here suggest that caution be used in categorizing these three groups as either competitive or non-competitive without further reflections, and possibly further research.

Analyzing the above results in terms of average concentration levels (see Table 14), it would appear that high-concentration industries are more likely to be non-competitive, with 5/8 (or 63%) consistent or non-comparable NC outcomes and 3/8 contentious outcomes (i.e., where one method classified the industry as NC and the other as C). If we assume that the two methods, if in conflict are equally likely to be right, this means that high-concentration industries are likely to be non-competitive 80% of the time.

On the other hand, consistent results for low-concentration industries are: 3/9 non-competitive and 3/9 competitive. Allowing again for the 3 contentious outcomes to be one way or the other half the time, this means that the low-concentration industries were non-competitive only 50 percent of the time. Hence, whereas technical change differentials and returns to scale measurements were rather uninformative in explaining the concentration-cost effect observed in the previous section, these results indicate that high-concentration industries are more likely to produce at levels where average costs are not minimized than low-concentration industries. So the tendency of costs to rise as concentration rises in high-concentration industries may be due to the effect these industries subsequently producing at even more inefficient levels of production. The effect of increases low-concentration industries is less troublesome, since this group is more likely to be producing around the optimal output level anyhow.[33]

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[33] There is some danger here in associating divergences from optimal output levels with concentration. First, the possibility that the actual output level might be in 'error' - since it is not optimal - implies that this variable is stochastic, a violation of econometric assumptions implicit here. Second, if concentration levels are in fact related to output levels, as suggested by this comparison, covariance of these variables might pose bias problems if such relationships are not proved to insignificantly affect the accurancy of a model such as (14) and (13).

5. CONCLUSIONS

5.1 Summary of Results

In the three studies which comprise this paper we have limited our scope to two main questions: (1) how do differences in structure (i.e., the range of possibilities between perfect competition and monopoly) affect performance, as measured by productivity and profitability and (2) how do changes in this structure affect the same variables? Here we shall briefly recapitulate the results from each investigation.

Our first study, which used firm-level data, yielded enough evidence on cost differences, profitability differences between firms and other structural and explanatory variables between industries, to allow us to classify 16 food and beverage industries into the following groups:

1) **Workably Competitive (low overall profitability, similar firms)**
   - meat processing (but high turnover means profits understated)
   - poultry processing
   - dairy products (even though non-tariff trade barriers protect it)
   - feed industry
   - bakeries (despite internal differences in profitability)
   - sugar processors (despite large, concentrated firms)
   - vegetable oil mills

2) **Heterogeneous Costs (best firms much more profitable than average)**

- fish products (high exports may reflect cheap inputs)

3) **Market Power with Heterogeneity (high profits overall, but with some unusually successful firms)**

- fruit and vegetable canners	(strategic groups distinguish firms)
- frozen fruit and vegetables	
- flour and breakfast cereals	(high advertising in cereals)
- confectionery	(high advertising)
- soft drinks	(big gap between major brands and the others)

4) **Pure Market Power (all firms do well)**

- biscuits	(brand loyalties)
- distilleries	(heavy advertising, plus protected by provincial policies)
- breweries	

The results from this classification procedure suggest the following recommendations with respect to policy.

'Workably competitive' industries are not a priority for further investigation. It can be presumed that competitive forces in these markets are adequate to protect consumers and to discourage producers from letting costs rise, or from colluding to increase prices.

'Heterogenous costs' industries would be interesting subjects for further investigation, since sources of differential cost performances are still unclear. If this is due to factors in inelastic supply, such as unusually favourable natural locations, or a particularly brilliant entrepreneur, then no policy action is called for. But if heterogeneity stems from artificial factors, such as unequal access to inputs, or from more-or-less nonsystematic differences in the rate of adoption of new technology, then fruitful policy action might be possible (in the former case this could involve the application of competition policy; in the latter, an extension program).

In the cases where 'market power' and 'market power with heterogeneity' applies, competition policy may also be called for when price-raising market power is identified as the source of higher-than-competitive profits. Existing legislation, however, may not be sufficient to counter market power effects, and so other, more indirect policies (such as closer monitoring of profits or higher taxes) may be necessary to ensure a more competitive environment.

The second study (see Chapter 3) was concerned with the source of productivity growth or decline in the 15 industries studied. We compared the relative importance of productivity changes due to changes within firms (or the groups we looked at) against those due to changes in firms shares of total industry output.

We found that differences across industries were primarily due to the former effect, rather than the latter. Although there was quite a lot of mobility of firms between 'high' and 'low-' profit segments of their industries we concluded that differences across industries in productivity growth seem to have been largely due to differences in productivity performance with firms in the industries (rather than to shifts in the structure of output between high/low productivity operators).

In relation to all-of-manufacturing, average annual productivity growth, we found considerably lower productivity growth rates in all food and beverage industries studied. In fact, in some industries, costs actually rose, indicating a deterioration in efficiency over the period (1970-1979).

In the final study, we investigated the existence and magnitude of the effects of industrial concentration changes on costs of production for 17 of the Canadian food and beverage industries. We found that changes in concentration (the distribution of output shares between firms within an industry) did indeed affect average costs of production for these industries. Specifically, it was found that increases in concentration led, in general, to a decrease in average costs within low-concentration industries (i.e., those with average Herfindahl indices of concentration < 10). On the other hand, increasing concentration resulted in increases in average costs for high-concentration industries (i.e., those with average Herfindahl indices > 10). We also looked at some possible sources of the effects. Most directly, it was found that concentration changes had had a strong effect on the choice of inputs employed in production. For most industries, concentration increases increased the use of capital; employment of production workers was similarly affected. The results for energy and materials were more mixed, with positive and negative effects in roughly equal proportions for both across industries, while, interestingly, for salaried employees, it was found that increases in concentration generally led to decreases in employment for this group. When we combined the two employment effects and compared these between low- and high-concentration industries, an interesting trade-off between the impacts of concentration on efficiency and employment was revealed. Although increases in employment occurred in the majority of cases, the negative effects which were generated were only in the low-concentration industries. Thus, while increases in concentration led to efficiency gains for this group, this was achieved at the cost of lower employment. Similarly, while for high-concentration industries, increases in concentration might have been bad in an efficiency sense, they may have increased employment.

In terms of other indicators, however, there was little evidence of consistent differences between low and high concentration industries. We found that returns to scale and technical change (productivity change) effects were small, with no clear pattern of behaviour between the two groups. Nevertheless, we were able to identify some cases where industries consistently produced at higher or lower output levels than those dictated by theory to be optimally efficient, suggesting long-run non-competitive behaviour in these industries.

5.2 Conclusions and Policy Recommendations

The techniques used in all these studies could probably be refined and errors certainly will have been made, but there does appear to be some consensus about which industries or types of industries deserve further attention from a public policy standpoint and those which don't. Of the 17 industries examined, we found that the following industries have displayed non-competitive behaviour (using the criteria outlined in Chapter 4, Section 4.6.3.4):

- Fruit and Vegetable Processors
- Flour and Breakfast Cereals
- Biscuits Manufacturers
- Confectionery Manufacturers
- Soft Drink Manufacturers
- Distilleries
- Breweries.

In all of the above industries there was evidence of both market power and persistent inefficiency (i.e., production at suboptimal or supraoptimal output levels for all or most of the years studied), suggesting that move towards further concentration of production in these industries ought to be discouraged. These results are confirmed when we consider the effects of concentration in these industries directly: increases in concentration tended to increase costs in all but the fruit and vegetable and soft drinks industries.

We also found that only 4 industries could be clearly classified as competitive and of little interest from a regulation viewpoint, these are:

- Poultry Processors
- Dairy Products
- Feed Mills
- Vegetable Oil Mills.

For the dairy products and feed mills industries, concentration increases resulted in lower costs; costs tended to increase with concentration in the poultry processors and vegetable oil mills industries.

The four industries which we can less conclusively identify as having been competitive or non-competitive are:

- Slaughtering and Meat Processors
- Fish Products
- Bakeries
- Cane and Beet Sugar Processors.

These four are so difficult to classify that they really deserve further analysis.

Other results suggest that, in general, increases in concentration in high-concentration industries would tend to lead to further inefficiencies in these industries, while the opposite was true for low concentration industries. From an efficiency viewpoint, then, such trends should be discouraged. This would seem to be particularly true in the assessment of potential mergers in industries where concentration is already high (i.e., with Herfindahl indices > 10) and where we show that costs will rise if concentration rises. The industries which fall into this category are:

- Slaughtering and meat processors
- Flour and breakfast cereals
- Biscuit manufacturers
- Confectionery manufacturers
- Cane and beet sugar processors
- Vegetable oil mills
- Distilleries

- Breweries
- Wineries.

Of this group, we would expect mergers in five of the industries to also involve increases in market power, with market power effects based on our classifications noted in (3) and (4) of Section 5.1:

- Flour and breakfast cereals
- Biscuits manufacturers
- Confectionery manufacturers
- Distilleries
- Breweries.

Movement toward mergers in any of the latter five industries would seem to warrant discouragement if not direct prevention. This policy prescription must, however, be weighed against the possible opposite effects when employment numbers are considered. The apparent social costs of an inefficiency might be offset by improvements in employment, although it is hard to say which is likely to be greater than the other without further analysis. Either way, such possible overall gains would have to be weighed against almost definite increases in price distortions (through increased market power).

Overall, productivity improvement (technical change) in the food and beverage sector was markedly lacking when compared with that for all-of-manufacturing. Although there was little evidence of overall improvement in the majority of the industries studied (and a number of cases where productivity deteriorated), there have been significant changes in the way in which inputs are used due to the adoption of new technology. In particular, technologies were introduced which use more materials and energy relative to labour. The apparent technological bias against labour is worrisome, given the existing levels of unemployment in Canada. This evidence would suggest that if employment is a concern, this bias ought to be better understood, and perhaps discouraged.

The poor productivity performance of this sector relative to all-of-manufacturing suggests that the way in which input choices and technology choices have been made in food processing may be an issue which deserves further attention. Perhaps the bias towards materials and energy and away from labour in these industries has been more costly than firm-managers had originally expected when they invested in labour-saving technology. Improvements in materials use (maybe through more judicious use of packaging - food and beverage industries account for 60% of packaging materials used in all-of-manufacturing in Canada (West 1987, p. 16)) is one obvious area where costs might be reduced. Certainly, the apparent bias against non-production labour in these industries (both in terms of substitution for it by capital and movement away from it with adoption of new technologies) has not led to an improvement in costs.

In conclusion, we recommend that policies be focussed upon the first group of industries in order to prevent them from becoming more non-competitive (more like monopolies) and perhaps to encourage them to behave more efficiently and lower prices accordingly. The second group appears to have displayed competitive behavior; little additional attention is required for these industries - the only concern is that they remain competitive. For the third group of industries, we identify four cases where further analysis would seem to be warranted, especially regarding the likely effects of mergers on costs for slaughtering and meat processors and cane and beet sugar processors. Similarly, mergers proposed in any of the industries in the fourth group are likely to result in lower efficiency. In the last group, it would appear that mergers which would lead to greater concentration ought to be vigorously prevented since they are likely to lead to both greater market power and lower efficiency, thus unequivocally making society worse off.

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APPENDIX 1: DESCRIPTIONS AND SOURCES OF DATA USED IN ESTIMATION OF TRANSLOG COST FUNCTION

The data used in estimation of the cost/share system (14) and (13) include: total costs (i.e. the sum of capital, production labour, non-production labour, energy and materials costs); cost shares for both labour inputs, energy and materials; price indices for all five inputs; a gross output quantity index; a concentration (Herfindahl) index; and a trend variable. The data set is comprised of a 22 year (1961-1982) time-series for each of the 17 4-digit food and beverage industries, giving a total sample size of 374 observations. Each varaiable is briefly described below.

Capital cost and price data were estimated using capital stock, rate of return, depreciation and capital price series or data points. The capital stock data were adapted from a 1960-1975 4-digit and 1960-1982 3-digit series prepared by the National Wealth and Capital Stock Section of Statistics Canada's Science, Technology and Capital Stock Division. The former series was provided to Agriculture Canada in 1975 on special request and is not available from any Statistics Canada publication, to our knowledge[1]. This series was extrapolated to 1982 using a procedure described in detail in Cahill (1986). The completed 1960-1981 series employed is defined as year-end net stocks (i.e., of construction, machinery, and equipment stocks aggregated to a single value) and is in nominal (current) dollars.

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[1] Landry, R.J. (pers. comm.): correspondence between Ms. Pamela Cooper (Food Markets Analysis Division, Agriculture Canada) and Mr. R.J. Landry (Chief of National Wealth and Capital Stock Division), August 30, 1985.

Following Berndt and Christensen (1975) we use after-tax corporate rate of return information to calculate opportunity cost of holding capital. Our data are drawn from Peprah (1984) and are annual rates of return net of all taxes except personal income taxes but with depreciation rates adjusted to reflect their economic instead of accounting values.[2] We use all-of-manufacturing rather than food and beverage industry rates of return to avoid the inclusion of industry-specific rents, and average these over 1965-1981 (the period covered by Peprah). This average is then applied to the capital stock for each year and for all 17 industries (see Cahill (1986, pp. 108-111 for justification). The average used is 10.69 percent.

For depreciation rate, we also use a single point, adapted from Denny, Fuss and Waverman (1979); it is 6.6 percent.[3]

For the price of capital we use the "price index for capital expenditure on plant and equipment" (total components), which is a 1961-1982 time series for the whole of food and beverage industries (i.e., at the 2-digit level of aggregation) and scaled to 1971=1. This was obtained from Statistics Canada catalogues 13-568 ("Fixed Capital Flows and Stocks": occasional) and 13-211 ("Fixed Capital Flows and Stocks": annual). Because these data are so aggregated (i.e., to the 2-digit level and for all components) they are less than ideal, but are the best we had at our disposal.

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[2] Peprah (1984) found that the use of depreciation rates used by corporations (in manufacturing) in their financial statements created a bias which decreased "the reported rate of return by approximately 6.92 (nominal) percentage points on average ..." (p. 58) for 1965-1981.

[3] Again, see Cahill (1986, p. 111) for more discussion.

The data described above are used to generate the two capital variables used in estimation: the cost of capital services (used with the cost of other inputs to calculate total costs of production and

thereby cost shares for the other four factors), and the price of capi (which enters both the cost and share equations). The cost of capi services is estimated (for each industry) as follows:

$$(1.1) \qquad C_{kst} = (r + \delta) \cdot KS_{t-1} \quad ; \; t = 1961, 1962, \ldots, 1982 \; ,$$

where: C_{kst} is the cost of holding stock in period t,

r is the nominal rate of return (assumed constant over the period in question),

δ is the economic depreciation rate (also assumed assumed to be constant), and

KS_{t-1} is the value of the end-year net capital stock from the previous period (in current dollars).

Note that because end-year stocks are being used, and since investment is assumed to occur at year-end, the cost of capital in year 1 will be a function of the value of capital stock at the beginning of year t (i.e., year t-1's year-end stock) and interest and depreciation rates in year t.

The price of capital equation employed is adapted from Jorgenson and Griliches (1967), who point out that "the prices of capital services must be calculated beginning with the prices of new investment goods" (p. 255). The capital price series used here are derived using the relationship:

$$(1.2) \qquad w_{kt} = q_{kt} \cdot (r + \delta) \quad ; t = 1961, 1962, \ldots, 1982,$$

where: q_{kt} is the price of one unit new capital at time t.

Since, for ease in estimation, all input price variables, the output index, and the Herfindahl index are scaled to 1971=1, the scaled capital price w^*_{kt} is:

$$(1.3) \qquad w^*_{kt} = \frac{q_{kt} \cdot (r + \delta)}{q_{k1971} \cdot (r + \delta)} = \frac{q_{kt}}{q_{k1971}}$$

$$= \frac{pcap_t}{100} \quad ; t = 1961, 1962, \ldots, 1982.$$

where: $pcap_t$ is the capital price index described above (i.e., as taken from Statistics Canada catalogues 13-568 and 13-211).

As opposed to the capital cost data which differed between industries and time periods (1.3) only differs between time periods (as does (1.2)) for reasons already discussed. Note also that the term $(r + \delta)$ drops out of (1.3) since this term is assumed constant over the period studied.

Data for the two labour variables used (production and non-production (salaried) labour), as with the data for energy, materials and output, were provided by the Food Markets Analysis Division of the Policy Branch, Agriculture Canada. The labour variable descriptions are as follows:

1. person-hours worked by production workers ('000)
2. total wages of production workers ($ '000)
3. number of non-production (salaried) workers
4. total salaries of non-production workers ($ '000)

The data are for 1961-1982 for each of the 17 4-digit industries. Wages and salaries data are in current dollars. The series were obtained from the Census of Manufacturers of Statistics Canada and most of them are published in the Statistics Canada publication "Manufacturing Industries of Canada: National and Provincial Areas" (catalogue 31-203, annual). Since the first data series (person-hours worked by production workers) is not published, the data were obtained from the public tape of the Census.

Items 2 and 4 above give the cost of production labour C_{1p} and non-production labour C_{1np} respectively. The average hourly (production labour) wage series for each industry is derived by the following identity:

$$(1.4) \qquad w_{lpt} = \frac{C_{lpt}}{Q_{lpt}} \quad ; t = 1961, 1962, \ldots, 1982,$$

where: w_{1pt} is the hourly wage at time t,
C_{1pt} is as defined by 2 above, and
Q_{1pt} is as defined by 1 above

Similarly, the average annual salary series for non-production workers for each industry is derived by:

$$w_{lnpt} = \frac{C_{lnpt}}{Q_{lnpt}} \quad ; \; t = 1961, 1962, \ldots, 1982, \tag{1.5}$$

where: w_{lnpt} is the average salary at time t,
C_{lnpt} is as defined by item 4 above, and
Q_{lnpt} is as defined by item 3 above.

Both prices are scaled to 1971=1 for estimation.

The data on fuel and electricity expenditures and prices for 1961 were obtained from industry publications of Statistics Canada (32-202 to 32-227), with data for Flour and Breakfast Cereals obtained by summing data from Flour Mills and Breakfast Cereal publications (32-215 and 32-204) respectively. Data for the 1962-1974 period were obtained from Statistics Canada publication "Consumption of Purchased Fuel and Electricity by the Manufacturing, Mining and Electrical Power Industries" (catalogue 57-506). For the 1975-1981 period the publication used is "Consumption of Purchased Fuel and Electricity by the Manufacturing, Logging and Electric Power Industries" (catalogue 57-208). For 1982, the data were supplied by R.J. Stavely of the Industry Division (Manufacturing and Primary Industries) of Statistics Canada, since these had not yet been published.

Total cost of energy (fuel and electricity expenditure), C_{et} in period t was obtained by summing the expenditures on the 7 energy input components (coal and coke, natural gas, gasoline, fuel oils, liquified petroleum gases, electricity, and 'other fuel'). Individual energy-type price indices were then derived by dividing their cost series by their quantity series (to obtain annual prices) and then divided each by their 1971 values so that the price series for each component was scaled to 1971=1. An aggregate price index (Fisher ideal), W_{et} for fuel and electricity was constructed using these price components. Again, this series covers the period 1961-1982 and is available for each of the 17 industries being considered, with W_{et} again scaled to 1971=1 for each industry.

Two series were used to construct the total cost and price data for materials: a constant-dollar value series of net material inputs (derived by subtracting energy costs from gross materials costs), and a current-dollar value series with the same definition. Both sets of data were obtained from the Industry Product Division of Statistics Canada. Although the data actually used are not published, comparable data at the 3-digit S.I.C. level are available from the Statistics Canada publication "Systems of National Accounts: Gross Domestic Product by Industry" (catalogue 61-213).

A materials price index was obtained by dividing the current-dollar values of materials (C_{mt}) by the constant-dollar values (CON_{mt}). Thus, for each industry, the price series is obtained by the identity:

$$(1.6) \qquad w_{mt} = \frac{C_{mt}}{CON_{mt}} \quad ; t = 1961,1962,\ldots,1982$$

As with the other four prices, this is also scaled to 1971=1 for each industry.

The output data used, Q_t, are a constant (1971) dollar series of gross output for each industry. These series were obtained from the Industry Product Division of Statistics Canada. Although these data are not published, once again comparable data at the 3-digit S.I.C. level are available from the Statistics Canada publication noted above for materials inputs. These data are also scaled to 1971=1 for each industry.

The Herfindahl data are drawn from from the Statistics Canada publication "Industrial Organization and Concentration in the Manufacturing, Mining and Logging Industries" (catalogues 31-514 (1986) and 31-402 (1980, 1982p)), for all industries with some S.I.C. concordance adjustments, for every other year from 1965-1982, excepting the 2-year gap between 1965 and 1968. Observations for 1958 are also available for some industries. To derive a continuous time-series for h, linear interpolation back to 1961 and between years of publication were required. In the first case, either the 1965-1968 'trend' was used, or else if a 1958 observation were given the 1958-1965 'trend' was employed. In the second case, the approach was the same.

In addition to the interpolation exercises, there was some conflict of concordance for the fruit and vegetable processing, dairy products and flour and breakfast cereals industries (S.I.C.'s 103, 104 and 105, respectively). The series for fruit and vegetable processors was obtained by using data for S.I.C.'s 1031 and 1032 (years 1970-1982) to arrive at a joint h-index. More specifically, the combined index was achieved by treating each industry (1031 and 1032) as if it were a single group of firms and exploiting the definition of h given in (11), i.e.

$$h_{103} = \frac{[h_{1031} \cdot (Q_{1031})^2 + h_{1032} \cdot (Q_{1032})^2]}{(Q_{103})^2}.$$

The data for the dairy products and flour and breakfast cereals industries (which were divided into S.I.C.'s 1050 & 1070 and 1240 & 1250 respectively for the years 1965 and 1968) were derived in the same way. Finally, note that these series are also scaled to 1971=1 for each industry.

The trend variable, t, is set equal to 1 for 1961 and 22 for 1982, increasing by an increment of 1 each year.

In order to obtain (nominal) total costs of production, the capital, production labour, non-production labour, energy and material costs are summed for each industry, i.e.:

$$(1.7) \qquad C_t = C_{kst} + C_{lpt} + C_{lnpt} + C_{et} + C_{mt} \quad ; t = 1961, \ldots, 1982.$$

The cost shares are derived as follows:

$$(1.8) \qquad S_{it} = \frac{C_{it}}{C_t} \quad ; i = lp, lnp, e, m \quad ; t = 1961, \ldots, 1982.$$

The set of industry time-series of total costs, 5 input prices, output, Herfindahl indexes, and 4 cost shares described in this chapter are sufficient to estimate the cost/share system (14) and (13).

LIST OF WORKING PAPERS PUBLISHED IN 1989

No. 1 The International Competitive Status of Canada's Milk Production Sector. Rick Phillips, James White and Peter Stonehouse. January 1989.

No. 2 The impact of Canadian Commodity Stabilization Programs on Risk Reduction and the Supply of Agricultural Commodities. G.C. Van Kooten, John Spriggs and Andrew Schmitz. February 1989.

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